The University of New South Wales

Faculty of Engineering

Monitoring and Interpreting Human Movement Patterns Using a Triaxial Accelerometer

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A dissertation submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

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Dedicated to Terry Gagen,

who encouraged me to think deeply of simple things.

Abstract

This thesis addresses the hypothesis that a single, waist-mounted triaxial accelerometer (TA) can be used to monitor human movement patterns in unsupervised, free-living subjects over extended periods, and that it can be used to quantitatively measure parameters that can provide clinical insight into the health status of the subject.

A rigorous theoretical and experimental understanding of the signals obtained from a TA is developed. The effect of the placement of the TA device on the waist is explored and a model relating device position to TA signal is developed for a range of postures and activities.

A classification framework for movement identification using the signals from a waist-mounted TA is presented. This framework is based on a hierarchical binary processing tree and is designed for real time use. An implementation of this framework for monitoring housebound patients is presented. Algorithms for detecting falls, distinguishing between activity and rest, classifiying transitions between different postural orientations, and for identifying periods of standing, sitting, lying and walking are developed. In evaluation studies performed in controlled laboratory conditions, every algorithm performed with better than 90% accuracy. Once movements are identified, movement-specific parameters sensitive to changes in functional status are extracted from the signal.

A two stage methodology for employing the accelerometry system in monitoring free-living subjects is introduced. The first stage involved monitoring specific movements through a directed routine. The second stage involved monitoring of free movement. Signals obtained from the directed routine are used to extract clinically relevant, movement-specific parameters. Signals obtained from the period of free movement are monitored for falls and other abnormal events. General parameters of movement, including energy expenditure, are also measured.

The system was evaluated in a series of field studies in laboratory and home environments, in supervised and unsupervised settings, using cohorts of healthy subjects. A pilot trial was conducted in which six healthy elderly subjects wore the TA device for a period of up to three months. The technical performance and useability of the system were evaluated. Clinically significant parameters were measured and the effects of age and health status on the measured parameters were evaluated.

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Certificate of Originality

I hereby declare that the work in this thesis is my own and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by others, with whom I have worked at UNSW or elsewhere, is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

Signature of Candidate

Acknowledgements

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Chapter 1

Introduction

1.1 Vision Statement

The vision of this research is to provide a system for delivering health monitoring support to housebound people, particularly those who live alone, including the frail elderly and those with chronic disease. There are two primary aims:

1. to automatically detect adverse events such as falls and to generate an alarm, and

2. to monitor clinically sensitive parameters of movement in order to identify early changes in falls risk and health status.

It is believed that this system could be used to promote independent living by

- providing increased peace of mind to housebound patients and their families;

- calling for aid if an adverse event such as a fall occurs; and

- providing objective, patient-specific information in a timely manner that allows targeted interventions to be introduced to prevent further deterioration in health.

The work contained in this thesis provides a fundamental framework for achieving these aims. The triaxial accelerometer has been demonstrated to be a practical instrument for long-term, unsupervised monitoring of human movement. Exceptional events, such as falls, can be identified in the data from the triaxial accelerometer. Important movements and postures, such as standing, lying and walking can be identified in the data and clinically significant parameters can be tracked longitudinally. The work of this thesis provides both the methodology required for and implementations of real time human movement monitoring in an unsupervised setting, using a triaxial accelerometer.

1.2 Research Motivation

A growing problem in current healthcare is that healthcare costs are increasing at an unsustainable rate, and acute hospitals are becoming overburdened and unable to meet the demands that are being placed on them.

This has led to an interest in alternative approaches to health care delivery, which may be able to reduce costs and demand on hospitals, while not compromising the quality of care being delivered. One such approach is home telecare, the remote delivery of health care to the patient at home.

Monitoring human movement can provide valuable information on a patient. Parameters of movement can provide information on health status, functional ability, rate of rehabilitation, risk of falling, and other potentially useful clinical data.

It has been proposed that accelerometry, a technique that is increasingly being used for monitoring human movement in laboratories and research studies, is suitable for long term monitoring of human movement [31, 72, 76, 173, 201, 221, 225, 242].

The question that then arises is whether or not accelerometry can be used in a home telecare system to monitor movement in an unsupervised home setting.

1.3 Research Hypothesis

The hypothesis of the current work is that accelerometry is a suitable technique for monitoring human movement patterns in unsupervised free-living subjects over extended periods, and that it can be used to quantitatively measure parameters that can provide clinical insight into the health status of the subject. This hypothesis is addressed through the development of a accelerometer-based system that is suitable for human movement monitoring. Automated techniques for interpreting the data captured by the system in terms of human movement are devised and evaluated. Once the activity is classified, relevant parameters are extracted and tracked longitudinally. The functionality of the system is evaluated over a domain of basic daily activities and postural orientations performed by healthy subjects.

1.4 Considerations in Unsupervised Assessment of Human Movement

Any technology for unsupervised health monitoring must satisfy a number of general requirements:

- the implementation must be driven by clinical need, not driven merely by the existence of a new technology;
- it must function reliably;
- it must provide medical benefit;
- it must ensure the security of personal data;
- it must minimise inconvenience to the patient;
- it must be cost effective; and
- it must be acceptable to both patients and health care workers.

Above all, the technology must meet the specific purpose for which it was intended. In order to do this, the technology must be appropriate for the purpose. In a six step, iterative framework for the assessment and evaluation of home telecare systems, Magrabi [153] noted that before proceeding with any system development, the problem must be clearly defined and examined to determine whether the introduction of a home telecare system is an appropriate means of addressing the problem.

Given the problem of an ageing population leading to an increasingly expensive and unsustainable health care system, the need for an alternative health care approach is evident. A home telecare health monitoring system is an alternative that has several desirable features:

- The patient can be monitored in the natural home environment. This provides real information on how the patient performs at home, which can differ from performance in a clinical setting.
- Home monitoring can provide patients with the security that they need to continue living independently at home. Most people prefer to remain living at home, especially if this is an alternative to nursing home care [204].

- Data can be collected more regularly using an automated home monitoring system, and with less inconvenience, than if clinical visits are required for data collection. The more regular monitoring can also assist in maintaining health by detecting early changes in health status.

An important aspect of health is functional ability—the ability to carry out routine daily activities. The current work is concerned with objective monitoring of functional ability by means of a home telecare system that monitors human movement and then extracts relevant clinical information from the signal.

Since accelerometry has been successfully used in laboratory settings, and has been hypothesized to be appropriate for use with free-living subjects it is appropriate to consider its use in a home telecare setting.

In order to assess the utility of an accelerometry-based home telecare system for unsupervised monitoring of housebound patients, it is first necessary to design a system that meets all of the requirements listed above. In particular, it must be noted that accelerometric monitoring requires a device to be attached to the patient and this requires patient compliance. There are many factors that can reduce the level of patient compliance, including the cost involved in purchasing and maintaining the system, difficulty in using the system, inconvenience, discomfort, confusion in understanding how the system should be used, and forgetfulness [23].

A device that is to be worn over extended periods must be designed to be as simple to put on and as comfortable to wear as possible in order to encourage compliance. A system with multiple sensors placed across the body can provide superior data to a system that has only a single sensor location. However, such a system will be more time-consuming and thus more inconvenient to put on and wear, which will lead to reduced compliance rates. There is also an increased risk of confusion resulting in the patient incorrectly placing the sensors. The accuracy with which wearable devices need to be attached will also affect compliance. Devices that require precision in placement will be more likely to be subject to incorrect placement or reduced compliance in use due to the difficulty of attaching the device. A device that can tolerate some flexibility in placement is preferred on these grounds.

1.5 Application of Accelerometry to Unsupervised Ambulatory Assessment of Human Movement

The application of accelerometry to monitoring of human movement has only become practical in the last decade with the development of new accelerometer technologies. The application of accelerometry to unsupervised monitoring of human movement is still relatively novel and there is limited knowledge available on its suitability or on data interpretation methodologies.

In the current work a single instrument contained in a pager-sized case was used to monitor human movements. This system was designed to be inexpensive, simple to use, and as unobtrusive as possible. Three-dimensional accelerometry was employed to monitor movements of the subject. The focus of the work was on understanding the signals produced by this device and interpreting them in terms of human movement, and in identifying clinically relevant parameters from the data.

The analysis and algorithmic development that was undertaken in the current work was based on data taken from healthy young and elderly adults. The results obtained provide normative baseline data and algorithmic parameter sets tuned for normal subjects. This provides the basis for future work in which data can be collected from specific housebound subject groups (such as the frail elderly, or people with congestive heart failure) and compared to the results for normal subjects.

There are obvious limitations to using only accelerometry and measuring at only one point on the body. It is not possible for a single instrument system to accurately identify exactly what a person is doing all of the time. For example, if the device is attached to the torso then the system is not responsive to activities that involve limb movements but not torso movement (e.g. cycling or washing the dishes). However, the purpose of the system is not to replace a detailed clinical assessment. Rather, the purpose of the system is to monitor the patient over extended periods in order to identify abnormal movements (such as falls) and changes in parameters that are sensitive to changes in health status. Thus it is designed to be an automated alert and early warning system.

In this context it is not necessary to have a complete classification of the patient's movements, provided that the system is able to detect abnormal movements, and can extract and track clinically sensitive parameters. These parameters, which include sit-to-stand transfer time and walking cadence, are addressed in later chapters (chapters 6–8).

There are several activities that are fundamental to independent daily living, and which provide valuable information on functional ability. Two activities of particular importance are walking and transferring (changing posture from sitting to standing, or from lying to sitting, and so on). It is also valuable to know the postural orientation of the subject, which can be broadly classified as standing, sitting or lying. Metabolic energy expenditure and the overall amount of time spent in activity (as opposed to rest) during the day also provide useful information on health status. The current work focuses on automated identification of important activities and postural orientations from the signals obtained from a wearable accelerometer device, and on the extraction of clinically relevant parameters.

1.6 Objectives of the Current Work

The aim of the current work is to assess the feasibility of using a simple, low-cost, wearable, accelerometer-based device to measure human movement in an unsupervised home environment.

The specific objectives of the work are

1. to establish the requirements for an accelerometric home monitoring system, and to provide a functional specification for such a system;

2. to develop an understanding of the data produced by a waist-worn, triaxial (three-dimensional) accelerometer during human movement;

3. to develop a framework for the interpretation of the data provided by an accelerometric home monitoring system;

4. to develop a classifier to identify falls, basic activities and postural orientations;

5. to develop algorithms to extract relevant information from the data in a real-time setting;

6. to undertake a field trial of the system in an unsupervised home setting;

7. to evaluate the useability of the system for unsupervised home monitoring; and

8. to evaluate the effectiveness of the algorithms and the data interpretation framework.

1.7 Outline of the Current Work

The current work contains three broad parts.

Part I provides a general background to the area of research. Chapter 2 reviews the statistics and the literature that provide the motivation for this research. Traditional and new methods of health care delivery are described. The importance of objective monitoring of human movement is discussed. Techniques for the assessment of human movement are reviewed and the choice of accelerometry for unsupervised home monitoring is established. In chapter 3 the use of accelerometry for monitoring human movement is introduced. Biomechanics and physiology of human movements at the centre of mass are introduced. Literature pertaining to the assessment of balance, sit-stand-sit transfers, and walking is reviewed, with a particular focus on the use of accelerometry. The use of accelerometers to estimate metabolic energy expenditure is reviewed. Studies in which accelerometers have been used to classify movements, and to detect falls are also discussed.

Part II encompasses the design of an accelerometric system for unsupervised monitoring of human movement. Chapter 4 discusses the functional and technical requirements for such a system, and introduces the data collection system that was used in the experimental studies of the current work. Chapter 5 develops an understanding of the data provided by the accelerometry system, both in a theoretical and in an experimental context. In chapter 6 this understanding of the signals is used to create a number of algorithms for interpretation of the accelerometric data. A framework to analyse and interpret the data is introduced.

Part III discusses the experimental evaluation of the accelerometric data collection and interpretation system. Chapter 7 provides details of the experimental design used in the field studies. The results and discussion of the experimental work are given in chapter 8.

The concluding chapters of the work provide recommendations for further research (chapter 9) and draw the main conclusions from the work (chapter 10).

Chapter 2

Motivation

2.1 Overview

This chapter describes the motivation for the current work. It provides background information on the current state of health care and alternative techniques that may lead to improved outcomes. The chapter is divided into three sections. The first section introduces the problem of providing health care to an ageing population, which is placing a heavy burden on the existing health care delivery system. Home telecare, an alternative health delivery paradigm, is presented. The importance of regular health monitoring in maintaining health and quality of life for housebound patients is discussed. Concepts of health and instruments for measuring health are described.

The second section examines the common conditions that afflict the housebound population, with a particular focus on the elderly, and discusses the potential benefit of monitoring human movement during routine daily activities. The techniques that are currently available for monitoring and assessment of human movement are reviewed in the third section.

2.2 The Health Care Problem

2.2.1 Introduction

Over the last decade there has been a growing interest in alternatives to the traditional model of health care. This has been brought about through economic pressures, the increasing demands being placed on hospitals due to an ageing population, and through a recognition of the importance of quality of life to health and a desire to improve quality of life for housebound patients. One alternative to traditional health care delivery is home telecare, in which health care is provided to the patient at home without a clinician or health care worker being present.

2.2.2 Defining Health

What is health? The concept of health has grown with the advancement of medical science. Originally health was considered only in terms of survival. Interventions were considered successful if they prevented mortality, and other factors were not taken into account [164]. From this beginning health has evolved to be defined as freedom from disease, then to an emphasis on the individual's ability to perform daily activities, and finally to an emphasis on happiness, social and emotional wellbeing and quality of life [164].

The Preamble to the World Health Organisation (WHO) Constitution states that "health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" [1].

Patients' views of health are in agreement with the WHO definition, in that social and emotional health are perceived to be as important as physical health. Sherbourne [197] states that

> "patient preferences, which should be driving treatment decisions, are related to mental and social health nearly as much as they are to physical health. Thus, medical practice should strive to balance concerns for all three health domains in making treatment decisions, and health care resources should target medical treatments that improve mental and social health outcomes."

One of the fundamental aspects of health, according to the currently recognised definitions, is quality of life. The factors that are considered essential for good quality of life vary from person to person although good health (physical, mental, social and emotional), functional independence and the ability to carry out routine daily activities are generally regarded as important.

Maintaining personal dignity is also very important to quality of life, and a large part of that is having the ability to make decisions about personal activities. This is a freedom that is often lost, at least to some extent, in hospital and institutional care settings. Moving into a managed care setting can also uproot a person from their established social networks and community activities. It is for these reasons that the majority of chronically ill, housebound patients and frail elderly patients prefer to live in their own homes rather than move into institutional care, despite the increased risks and difficulties associated with living alone [120].

2.2.3 Traditional Health Care Delivery Model

Medical care was traditionally provided by the physician to the patient in the patient's home. In the twentieth century, advances in medical technology changed the way in which health care was delivered. Patients now travel into the physician's office for treatment of routine illnesses and health conditions. For more serious acute illnesses and surgical procedures, patients are admitted to hospitals where they are treated by specialist medical staff.

Dedicated health care centres such as clinics and hospitals allow costs and resources to be shared amongst patients. This means that patients can have access to the best available medical technologies and can receive the best possible care (round-the-clock if in hospital) in a reasonably cost-effective manner.

There are some drawbacks to hospitalisation. Hospitalisation takes the patients away from their home environments and prevents them from carrying out any of their usual activities. It may negatively affect their social interactions, particularly if the hospital is not near the home. There are risks of infection, injury due to falling, loss of muscle tone leading to increased risk of injury on discharge, and other problems that occur as a direct result of hospitalisation [94]. An acute crisis and subsequent hospitalisation may be sufficient to send the frail elderly, those with a chronic disease, and those particularly susceptible to illness into a spiral of increasing illness, frailty and dependence. Even if this is not the case, considerable time and effort must be given to rehabilitation.

An even more significant problem with the traditional model of health care is that it is a reactive system. This model was designed for, and is appropriate for, the treatment of acute problems, but not for the management of chronic conditions, which are becoming increasingly prevalent in the community.

In this health care delivery model most community dwellers receive no medical care until the onset of an acute illness or the occurrence of an injury. If the condition is minor it is normally assessed by a general practitioner (GP) who will prescribe treatment. Once health is restored there is often no further contact between the patient and GP until the onset of another illness. In the event of more serious illness or acute health crisis the patient may be admitted to hospital.

During hospitalisation the patient is monitored regularly and her or his condition optimised through appropriate use of medication and other treatments. After treatment, the patient is discharged, often without a follow-up programme.

This health care model, which was designed for treatment of an acute illness or injury, can, in patients with chronic disease, result in recurrent hospital admissions and poor overall management of the condition.

Different, pro-active models in which measures are introduced that seek to prevent health problems from occurring or becoming worse are increasingly being used in conjunction with this model. Community-based health promotion and maintenance programmes have been receiving increased interest and support in recent years. Most of these programmes empower patients to take a more active role in their own health care through the provision of education and tools to enable health monitoring. Regular health monitoring forms an important part of such programmes. Regular monitoring enables changes in health to be detected, and hence treated, early. This allows the patient's condition to be maintained at close to optimal levels. Many patients with chronic illnesses manage their conditions at home, but insufficient health monitoring can mean that drug dosages and treatments may not be adjusted and optimised as the patient's condition changes, and this may lead to a deterioration in health that could have been avoided with better monitoring.

These shifts in methods of health care delivery are being brought about by an ageing population that is leading to escalating health care costs and increasing pressures on the existing hospital system, and also by a desire to use new technologies to enhance quality of life by providing health monitoring and assessment at home while not compromising the quality of health care. These two issues, health care expenditure and quality of life, are discussed in the following sections.

2.2.4 Demographics

Australia's population is ageing. Figure 2.1 shows the projected population increase by age group between 1996, 2020 and 2051. It can be seen that there is expected to be little increase in those below 50 years of age, but that the numbers of people over 50 years of age will increase substantially [51]. In 1998 there were 2.3 million Australians (12% of the total population) aged 65 years and over. This figure has increased from 9% of the population in 1976 [28], and is projected to rise to 6 million, or 24% by 2051. Similarly, those aged 85 years and over currently make up 1% of the population, but are expected to make up 5% of the population by 2051 [12]. There are currently over five people of working age for every person aged 65 years and over in Australia, but by the middle of this century there are expected to be only 2.5 people of working age for every person aged over 65 [27].

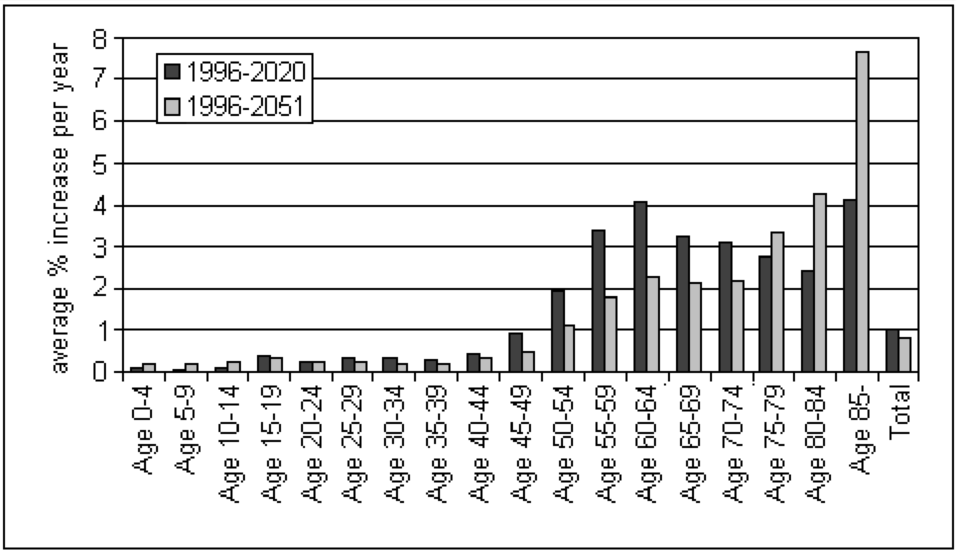


Figure 2.1: Comparison of projected annual rates of increase of Australian population by age over two periods: 1996 – 2020 and 1996 – 2051. Reproduced from Commonwealth Department of Health and Aged Care data [51].

Population ageing is a worldwide phenomenon brought about by a decline in fertility and an increase in life expectancy due to improved standards of living, hygiene and medical knowledge. Globally the number of older persons (60 years or over) will more than triple, increasing from 606 million today to nearly 2 billion by 2050. The increase in the number of the oldest old (80 years or over) is expected to be even more marked, passing from 69 million in 2000 to 379 million in 2050, more than a five-fold increase [15].

Australia has one of the highest life expectancies in the world at 75 years for males and 80 for females [28], and this is projected to reach 82.0 years for males and 86.1 years for females by 2051 [6].

In Australia, the number of births has remained almost constant but the population has increased due to immigration and increased longevity, causing an upward shift in the age demographic. There were also a large number of people born after the second world war (known as "baby boomers"). These people are now approaching retirement and will soon be counted as part of the elderly population.

2.2.5 Health Care Expenditure

Health is one of our most valuable assets, and this is reflected in the amount of money spent on health care services. The spending on health care services in de-

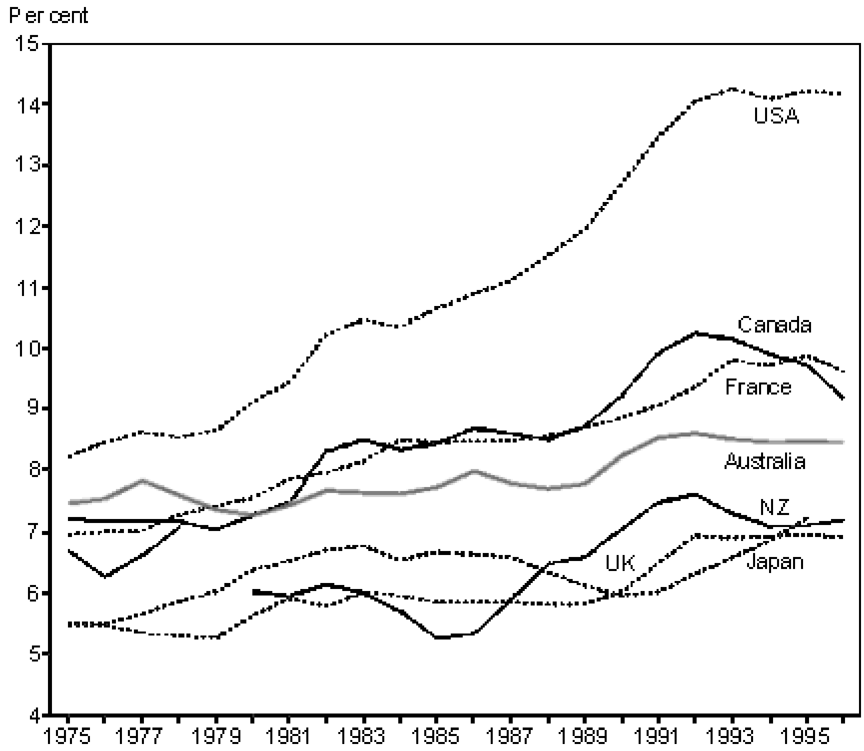


Figure 2.2: Health expenditure as a proportion of GDP for selected countries, 1975 to 1996. Reproduced from Australian Institute of Health and Welfare data [7].

veloped nations has been gradually increasing. Figure 2.2 shows health services expenditure as a percentage of gross domestic product (GDP) for a number of developed nations, including Australia, from 1975 to 1996. Australia spends around 8.5% of its GDP on health care services. The UK, New Zealand and Japan spend around 7% of their GDP, France and Canada spend around 10% of their GDP and the USA currently spends around 14% of its GDP on health care services.

In Australia, health care services expenditure has been growing at a relatively steady rate and is much less dependent on the business cycle than other sectors of the economy. Money is spent primarily on hospitals (36%), doctors' services (20%), pharmaceuticals (12%) and nursing homes (8%). Figure 2.3 shows a breakdown of Australian health care expenditure for the 1995-96 financial year.

In dollar terms, health care services cost Australia $44 279 million in the 1996-1997 financial year. This represented an average rate of expenditure of $2 536 per person. Between 1975-76 and 1996-97, real health services expenditure in Australia more than doubled, with an average real increase of 3.5% per annum [7].

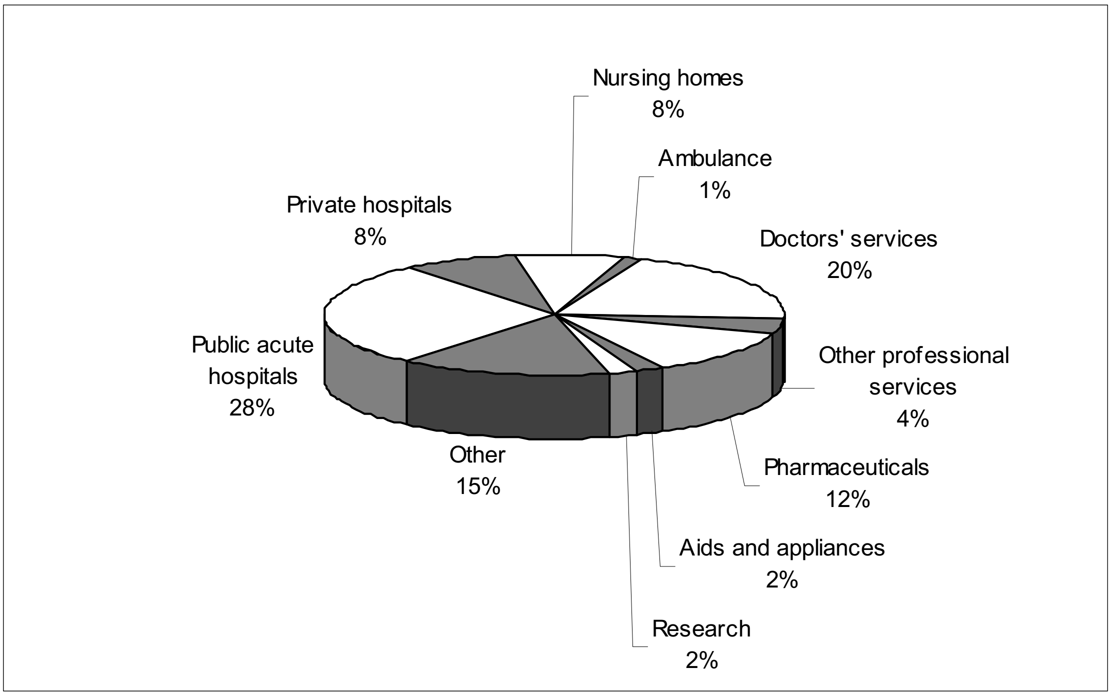


Figure 2.3: Distribution of health expenditure by category of expenditure, Australia 1995-96. Adapted from Australian Institute of Health and Welfare data [8].

Part of the increase in real health expenditure per person reflects greater use of health services by people of all ages. As new health care technologies become available, people expect a higher standard of care and this leads to increased costs. The other main component in the increase in health expenditure is the ageing of the population. Health expenditure remains relatively constant at about \$1200 per annum per person until around 50 years of age. Above 50 years of age, average annual expenditure rises from rapidly, as shown in figure 2.4. Hospitalisation and polypharmacy are major contributing factors to the costs of health care for the elderly.

On average, a person aged over 65 years spends four times as much on health as does a person aged below 40 years. In 1993-94 35.5% of health expenditure was on people aged 65 or above (12.1% of the population). The Australian Institute of Health and Welfare calculated that if the demographic predictions to 2051 are correct, then an additional \$10.39 billion in today's dollars will be required to maintain the same level and quality of acute hospital care as is available today, with about \$4 billion of this attributable to the ageing of the population. This is not a sustainable trend, nor can existing facilities support the demands that will be

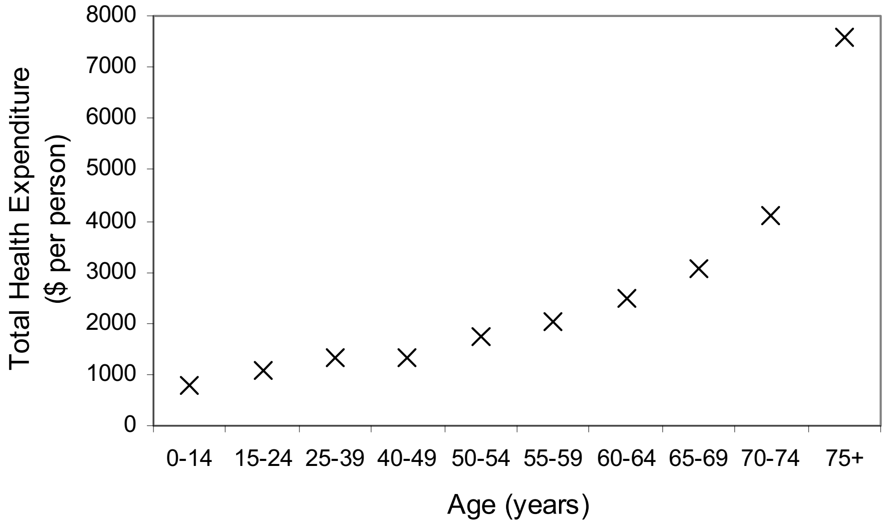


Figure 2.4: Total health care expenditure per person by age group (1989-1990). Adapted from Grant and Lapsley [86].

placed on them [7].

2.2.6 Techniques to Reduce Acute Hospital Admissions

The escalating costs of health care and the increasing burden being placed on the health care system by the ageing population have led to an interest in alternatives to acute hospital care. It has been shown that it is possible to reduce the length of hospital stays and to reduce the number of acute hospital admissions using new methods of health care delivery. There are a range of techniques that are able to contribute to this.

After a systematic review of the literature, the New Zealand Health Technology Assessment Clearing House (NZHTA) [5] concluded that

> "Good evidence exists (from randomised controlled trials) that the following interventions are effective at reducing [acute hospital] admissions: hospital at home schemes, comprehensive geriatric care, and the placement of GPs [General Practitioners] in the ED [Emergency Department]. It also appears that the introduction of various guidelines, certain new technologies and the provision of prospective funding have been proven to reduce admissions.

> "Some evidence exists that several other interventions are probably effective at reducing admissions. These initiatives include various public health interventions, home alarms, increased options for long-term care for the elderly, drug education for patients and practitioners, and hospital outreach services. The provision of senior staff in the ED and the development of ED-based observation units and chest pain units are also probably effective at reducing admissions.
>
> "Some interventions appear to be unsuccessful at reducing admissions although it should be noted that these interventions may still be able to improve other health outcomes. These ineffective interventions include: outpatient based education for individuals or groups, increased outpatient services, and utilisation review and case management."

Home telecare is a method of health care delivery that is associated with some of these interventions such as hospital in the home, home alarms and increasing options for long term care of the elderly. Home telecare is an alternative approach to health care delivery that has the potential to help reduce acute hospital admissions and to provide patient and economic benefit [208].

2.2.7 Home Telecare

Home telecare (which is also referred to as "tele-homecare", "personal telemedicine", and "telehealth homecare" [10]) is a special application of a method of health care delivery called telemedicine. The word telemedicine is composed from the Greek prefix *tele-*, meaning distance, or distant, and from the Latin, *medicus*, meaning a physician. Thus the term *telemedicine* can be defined to mean "medical care provided at a distance". Coiera [49] defines telemedicine as the "remote communication of information to facilitate clinical care". Bashshur *et al.* [22] state that a telemedicine system is one in which telecommunications and related technologies are used to "enable, facilitate, and possibly enhance clinical care and the gathering, storage, and dissemination of health-related information" when there is a "geographic separation between two or more actors engaged in health care".

In home telecare, telemedicine is used to provide health care to patients in their own homes, without a health care worker being physically present. The primary role of a home telecare system is to provide support to the patient [62]. Data are collected from the patient in the home, and provided to the health care worker via a telecommunications system. The data may be processed and analysed by the system before being provided to the health care worker, or they may be transmitted without

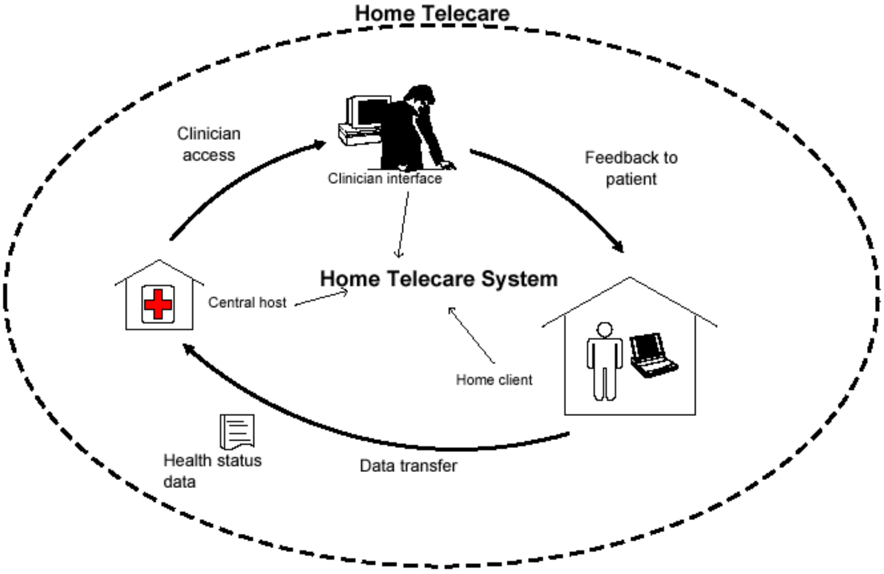


Figure 2.5: Illustration of a home telecare system. Home telecare encompasses the whole process of providing care in a community setting. A home telecare system is the technology employed to support the exchange of information. In this figure, the home telecare system comprises a home client, central host and a clinician interface. Reproduced from Magrabi [153].

having been processed. Figure 2.5 shows a generic home telecare system structure including the interactions between health care professionals and the patient by means of the home telecare system.

It has been hypothesized that home telecare techniques may be able to reduce the cost and/or improve the quality of health care by

- helping to avoid hospitalization;
- reducing the length of hospital stays—patients can be sent home earlier because of adequate levels of home monitoring;
- supporting and providing patient rehabilitation;
- facilitating independent living;
- sustaining health by preventing medical incidents through early intervention;
- reducing the number of visits that patients need to make to the clinic;

- allowing the provision of health care to patients living in remote communities; and by
- providing security against crises, such as falls, in the home [43, 62, 95, 125, 208, 231].

A number of studies have demonstrated improved outcomes with the use of home monitoring programmes [90, 95, 127]. However, preliminary studies on the economic advantage and overall benefit of home telecare have led to mixed results [54, 124]. This is due to the small number of studies, and the large variety of different types of home telecare projects, and the different health care funding models under which these systems have been introduced.

2.2.8 Applications of Home Telecare

Most home telecare systems fit into one of several basic categories.

Tele-consultation systems allow remote consultations between the health care worker and the patient, or between the health care worker and a specialist. These systems often use video or web-cam links to provide images during the consultation [24, 109, 118].

Patient Tele-Monitoring systems allow measurement of physiological parameters, such as heart rate and blood pressure. These parameters are transmitted to a clinician station, where a nurse or clinician can view the results [14, 16, 149]. This system for measurement of physiological parameters is often combined with a remote consultation facility.

Personal Emergency Response Systems provide a personal alarm that can be used in the event of an emergency. The patient wears a small unit with a push-button. In an emergency, the patient can press the button, which connects to the telephone via a wireless link and dials up an emergency contact to whom the patient can then speak without needing to reach the telephone [62, 192, 239].

Medication dispensing systems for scheduled dispensing of medications. Such a system consists of a medication storage compartment which holds a supply of tablets or capsules. When it is time for the patient to take some medications, the system emits an audible reminder to the patient about which medications to take, and in what quantities [206].

Unobtrusive monitoring systems provide longitudinal patient monitoring and automated alarm generation. These systems use sensors placed around the home to monitor the daily activities of the patient, such as cooking, toileting, watching television, etc. and generate an alarm when an abnormal deviation in the daily pattern is detected [43, 85, 198].

2.2.9 Home Telecare for Continuous Health Monitoring

Personal alarm systems are one of the few telecare systems that are currently commercially available for continuous health monitoring at home. Doughty *et al.* [62] describe these systems as first generation home telecare systems. They are entirely patient driven, they do not interpret data, nor can they automatically generate alarms. Second generation systems automatically generate alarms in the event of an emergency by means of continuous unobtrusive monitoring. Third generation systems encompass a more wholistic idea of health. In addition to health monitoring, they address social isolation, which is one of the biggest quality of life factors affecting housebound patients. Doughty *et al.* suggest that third generation systems will allow housebound patients to communicate with their peers through a virtual community, made possible by telecommunications technology.

Tang and Venables [208] further define a fourth generation of Internet-based systems to support home telecare. In these systems the Internet is used to facilitate monitoring, alarming, data transfer, data access and the "virtual" community.

Celler *et al.* [44] describe home telecare systems in terms of the level of support that the system provides to the patient. In this model the level of support provided is matched to the needs of the patient. Three basic levels of support are provided, and patients are encouraged to monitor and to manage their own health where possible.

The first level of support is preventive health care and education for self-management. This is directed at healthy people who want to learn ways to maintain their health. The primary purpose of first level systems is to use up-to-date medical knowledge to teach the patient techniques for health monitoring and maintenance.

The second level of support is for health maintenance. This is directed at people with pre-existing chronic conditions. In a home telecare system designed to provide this level of support, clinical instruments are provided to the patient for physiological monitoring at home. The results are made available to the patients' clinician. This level of home telecare is suitable for patients with a chronic disease condition that requires careful management (for example, congestive heart failure (CHF) or chronic obstructive pulmonary disease (COPD)) and for the elderly, in whom new morbidities associated with the chronic and degenerative diseases of old age are likely to emerge. Level two systems rely on regular patient participation in order to measure the physiological parameters. This level of compliance may be too onerous for particularly frail or ill patients, and is not suitable for patients with dementia.

The third level of home telecare systems provide support for patients who are not easily able to take an active role in managing their health, or are at risk of falling or becoming ill and being unable to raise the alarm for themselves. These correspond to second generation systems on the scale developed by Doughty. Level three systems provide continuous, unobtrusive monitoring by means of sensors placed either around the home [43, 85] or on the person [16, 237, 239]. The monitoring is combined with intelligent, real-time data processing to generate an alert if an adverse event occurs, or seems likely to occur. Level three systems are completely unobtrusive and provide continuous assessment of parameters.

Generally, the older a person becomes, the higher the level of support that is required. Figure 2.6 shows the three levels of support superimposed onto a graph of Australian health care expenditure by age group. As the cost of health care increases, indicating a greater level of health requirement, the level of support provided also increases. Preventative health care strategies are introduced when subjects are still healthy in preparation for old age. As health deteriorates, strategies for health maintenance and health support are introduced.

It may be beneficial for a subject to receive more than one level of support at the one time. For example, a patient with low-level CHF would benefit from regular physiological monitoring (level two) and also from educational materials on CHF and on maintaining a healthy lifestyle (level one).

There is some overlap between the three levels. For example, level two systems may provide feedback on health status to the patient, which acts as educational information for health maintenance. Another type of system, the wearable ambulatory monitor for unobtrusive monitoring, bridges the boundary between level two and level III systems (figure 2.7). A wearable ambulatory monitor is a level three system in that it provides continuous monitoring and patient input is not required to make these measurements. However, it is not a pure level three system in that patient compliance is required. The patient must decide to put on and wear the ambulatory monitor each day. Such devices also provide monitoring for health maintenance (both level two and level three function).

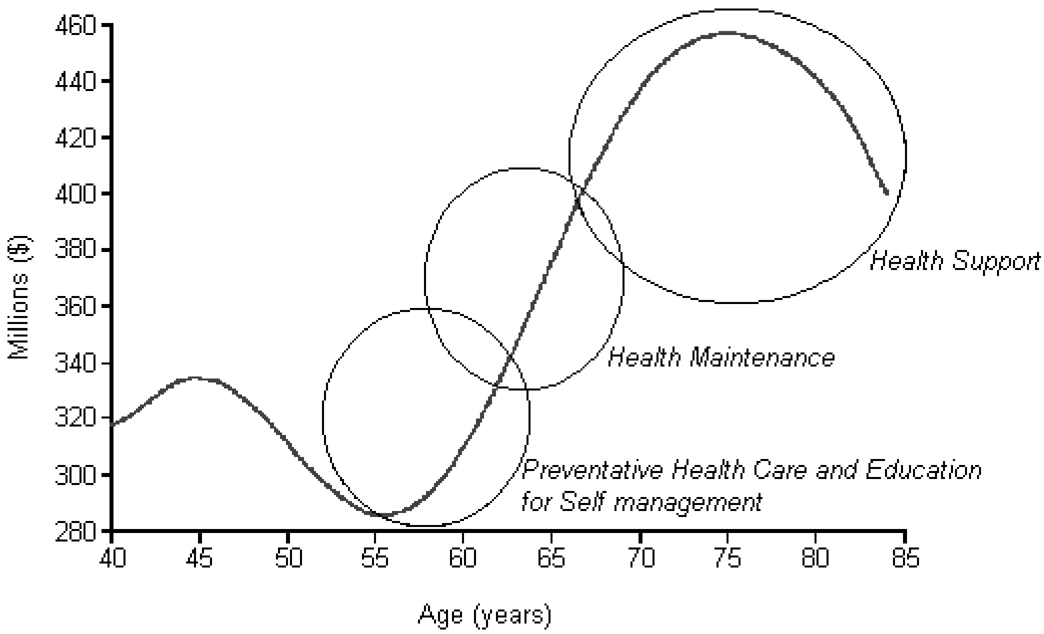


Figure 2.6: Australian health care expenditure by age (financial year 1989-90) showing the three levels of home telecare support. Reproduced from Celler *et al.* [44].

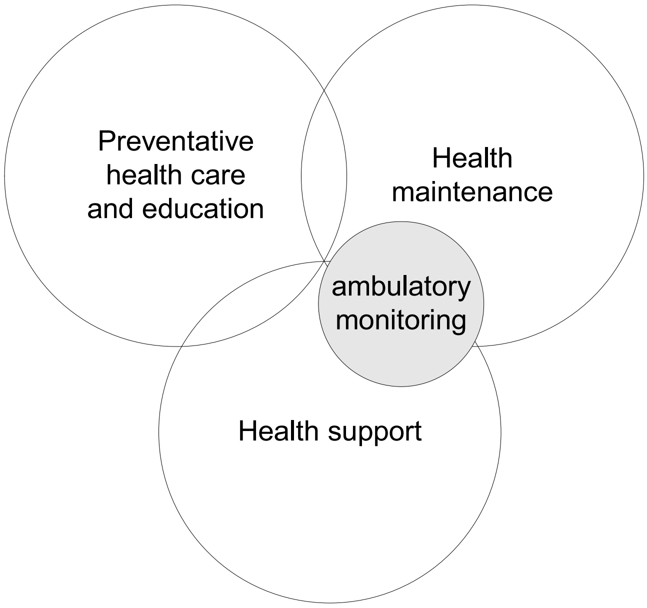


Figure 2.7: Overlap between the three levels of home telecare. Ambulatory monitoring using a wearable monitor overlaps between Level II and Level III support.

2.3 Health and Disease: The Case for Monitoring Human Movement

2.3.1 Introduction

As people age, chronic conditions, neurological disorders and frailty become increasingly prevalent. These factors, as well as affecting health, have a significant effect on functional independence and quality of life. These conditions are not limited to the elderly but they are more prevalent in older people, and so will become more significant problems as the population ages. Neither the chronic disease conditions nor the neurological orders are curable at the present time, but regular monitoring and careful management of the condition can promote health maintenance and quality of life by maintaining independence and avoiding morbidity.

2.3.2 Chronic Disease in the Elderly

Cardiovascular diseases are one of the leading causes of mortality in the elderly population [4]. They are also one of the main causes of acute hospital admission and readmission. 29.20% of all admissions and 38.12% of all readmissions to Prince of Wales Hospital (Sydney, Australia) in people over 55 years old in a 12-month period in 1998-1999 were for cardiovascular conditions, in particular, for congestive heart failure (CHF), chronic obstructive pulmonary disease (COPD) and ischaemic heart disease (IHD) [179].

IHD is a condition that affects the supply of blood to the heart due to the narrowing or blockage of coronary blood vessels. This can lead to myocardial infarction and is one of the most common causes of death. It is a condition that may have no noticeable symptoms. As many as three to four million Americans may have ischaemic episodes without knowing it [3]. On the other hand, CHF and COPD are debilitating diseases that gradually cause a deterioration in health, leading to death. As the disease progresses it has an increasingly profound impact on the patient's quality of life and functional independence.

In CHF the heart and the circulatory system are unable to meet peripheral demands, resulting in dyspnoea, fatigue, weakness, increased venous pressure, peripheral and pulmonary oedema. CHF is the leading cause of hospital readmissions in the elderly in the USA [129], where around 5% of 55-65 year-olds and 10% of those over 75 years suffer from CHF [113]. After the onset of CHF the median survival time for women is 3.2 years while for men it is 1.7 years [102].

COPD is the name given to a group of diseases, including chronic bronchitis and emphysema. They are chronic and slowly progressive respiratory disorders characterized by reduced maximal expiratory flow during forced exhalation. The most common symptoms of COPD are cough, increased sputum production, dyspnea, and wheezing. It is the fourth leading cause of death in North America, where as many as 10% of people over 55 years suffer from the disease [212]. After hospitalisation for COPD the average survival time is 5 years. Over the past 15 years, the incidence of COPD has risen more rapidly than that of any of the other leading causes of death, and it is the only one of the ten leading causes of death with rising mortality rates [212].

Both CHF and COPD lead to functional impairment and loss of independence. Moreover, patients with one of these conditions are particularly susceptible to other conditions that warrant hospitalisation and that limit independent living. The primary goals of health care in both cases are to prevent the further evolution of the disease, to maximize functional independence and avoid repeated hospitalisations. This is done by maintaining a careful balance between the benefit obtained from medications and the level of adverse side effects, and by proper exercise, nutrition and avoidance of infections. This requires close monitoring in order that treatment be successfully targeted. Inadequate supervision can lead to patient non-compliance, sub-optimal treatment and complications which lead in turn to hospital readmission and mortality.

Home care is becoming an increasingly viable and important way of providing monitoring and follow-up care to CHF and COPD patients. Intensive monitoring in the home has been found to decrease the incidence of hospitalisation and increase the functional capacity of elderly CHF patients [127]. Even low intensity home monitoring has been found to have a marked impact on the number of hospital admissions and the associated medical costs [95]. Patients feel that even simple, regular monitoring greatly improves their health status and their quality of life [149].

2.3.3 Neurodegenerative Disorders

Although cardiovascular disease remains the major cause of death in the elderly, the types of diseases prevalent in the elderly is changing. The age-adjusted death rate from cardiovascular disease (mainly heart disease and stroke) has decreased by 62% from 1968 to 1996 [4]. This reduction in the cardiovascular diseases is leading to the increased numbers of very old, and also to an increase in the presence of neurodegenerative disorders. Figure 2.8 summarises the trends in prevalence of traditional systemic disorders and neurodegenerative disorders amongst elderly community dwellers. When the longitudinal trends of prevalence are studied, rather than the actual prevalence at the current time, it can be seen that in the future, the neurodegenerative disorders will become a more significant problem in elderly health care than the cardiovascular diseases.

The neurodegenerative disorders associated with ageing are multifactorial, non-fatal, disabling disorders. They can be grouped into four broad categories:

1. motor instability and disorders of balance (leading to falls and social isolation),
2. cognitive impairment (e.g. the dementias, leading to loss of independence),
3. motor slowing (e.g. parkinsonism, leading to immobility), and
4. sensory impairment (disorders of vision and hearing, leading to disability and social isolation).

The syndrome known as "frail old age" is a complex mixture of these disorders. Broe *et al.* [2] predict that these disorders "will dominate as causes of severe disability and poor quality of life in the near future".

Treatment for these conditions consists of regular monitoring and intervention to sustain health and to prolong the ability to function independently.

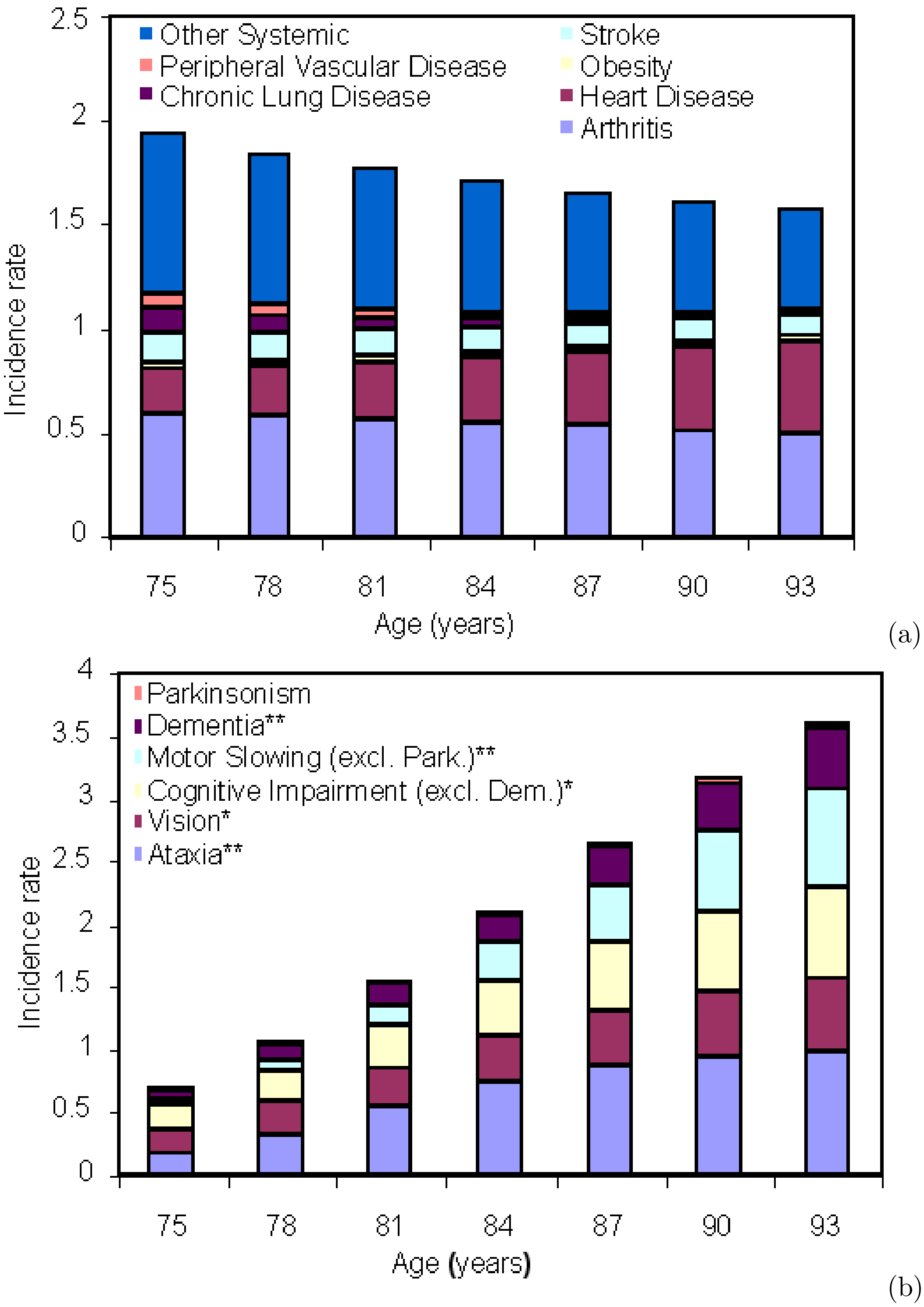


Figure 2.8: Three year incidence of (a) systemic disease and (b) neurosensory disorders in the elderly. $N = 353$, Age trends: * $p < 0.05$; ** $p < 0.01$. Figures provided by Prof. Tony Broe, Prince of Wales Hospital, Sydney. (Refer to [2] for similar data.)

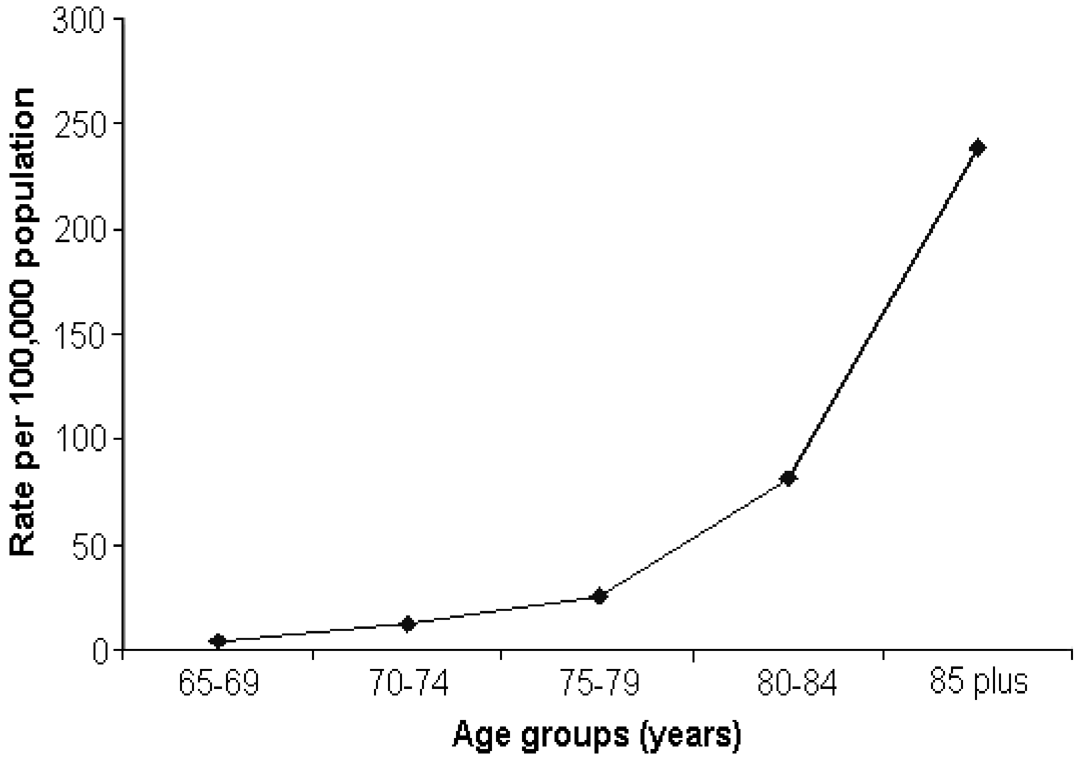


Figure 2.9: Age-specific rates of falls deaths for persons aged 65 years or more, Australia 1997. Source: Australian Institute of Health & Welfare, National Injury Surveillance Unit based on ABS Causes of Death. Adapted from Bishop [28].

2.3.4 Falls

One of the biggest risks to the health and wellbeing of the elderly is the risk of morbidity from injury, leading to functional dependence. Falls are a very serious risk for the elderly, particularly for those living in the community. In those aged over 65 years, two thirds of accidents are falls [94], and in the general Australian community, accidents are the fifth leading cause of death, and one quarter of them are falls [4]. Figure 2.9 shows the number of deaths due to falls in the Australian population as a function of age.

Around 30% of community dwellers aged over 65, and 50% of those aged over 80 years fall each year, and half of these people experience multiple falls [2, 216, 217]. The risk of falls increases with increasing age [29, 65, 146, 148, 216], due to multifactorial causes that may include neurological age-related changes, gait and postural changes, medical and psychological ill health, and the effects of medication.

Falls are the leading cause of injury-related hospitalization in persons aged 65 years and over, accounting for 54% of all injury hospital admissions in this age group [52]. Beyond 40 years of age, the incidence of fall-related admissions increases exponentially [140].

Up to 20% of those elderly who fall suffer moderate to severe injuries including fractures, joint dislocations or head injuries [133, 216, 217]. This equates to between 22% and 60% (depending on the population under study) of older people suffering injuries from falls [147].

One serious injury caused by falls is hip fracture. Elderly people recover slowly from hip fractures. In many cases hip fractures result in death and of those who survive, most never recover their earlier mobility [147, 158]. Other serious consequences of falls include death, loss of independence, hospital admission, and institutionalisation [64, 147, 217].

Falls are associated with functional decline in the elderly [65, 218], leading to disability, dependence, and nursing home admission [214, 217]. Downton [64] commented that "falls seem to be a marker of increasing frailty and risk of dying".

Even non-injurious falls create a loss of confidence in mobility in the older person [155, 215]. In a study of 1,103 elders by Tinetti *et al.* [215], 43% of community dwellers aged 70 years or older reported some degree of fear of falling, and 19% reported avoiding activities because of fear of falling. Many elderly people, having fallen once, become afraid of falling again, and so restrict their daily activities and exercise, which in turn leads to a further reduction in health and wellbeing [218].

Up to half of all older people who fall without suffering injuries are unable to get up without assistance. In a study of elderly fallers, Tinetti *et al.* [214] found that of 313 non-injured fallers, 148 (47%) reported inability to get up without help after a fall. An inability to get up after a fall results in a long lie if there is no one to provide assistance. Wild *et al.* [236] found that of 125 elderly people who fell in their own homes, twenty lay on the floor for more than one hour. Long lies of an hour or more are associated with fear of falling, muscle damage, pneumonia, pressure sores, dehydration, hypothermia and mortality [147, 214]. Moreover, fallers who are unable to get up are more likely to suffer a decline in activities of daily living, to be hospitalized, and to die [214].

In independent older community-dwelling people, half of falls occur within their homes and immediate surroundings [52, 61, 148]. Most falls occur in commonly used rooms such as the bedroom, kitchen and living room, and on level surfaces. Relatively few falls occur in the bathroom, on stairs or from ladders or stools (figure 2.10). Most falls occur during the day time and are in connection with routine daily activities [111].

As well as having an enormous detrimental effect on health and quality of life

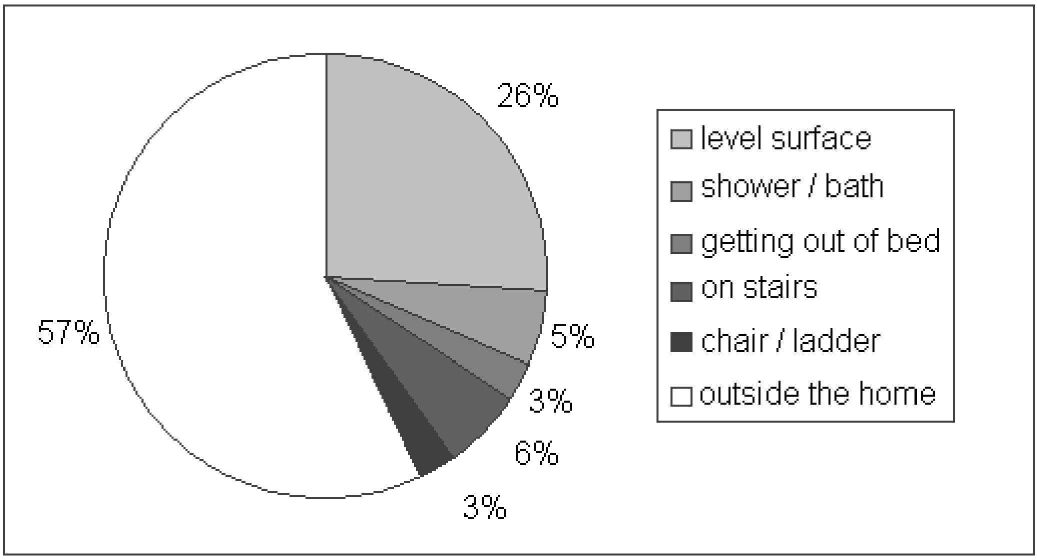


Figure 2.10: Locations in which falls occur. 56% of falls occur outside the home (in the garden, street, footpath or shops). The remaining 44% occur at various locations in the home. Adapted from Lord *et al.* [148].

for the faller, falls place a huge economic burden on the society. In Australia, the management of injurious falls is estimated to cost $AUD 2,369 million annually [13]. Similar costs have been reported in other developed countries.

Direct costs of falls include doctor visits, acute hospital care, nursing home care, outpatient clinics, rehabilitation, diagnostic tests, medications, home care, home modifications, equipment and institutional care. Indirect costs include carer and patient morbidity and mortality costs.

Rice and MacKenzie [190] evaluated the cost of injury in terms of the medical resources used for

1. the care, treatment, and rehabilitation of injured persons,
2. life years lost due to short- and long-term disability and premature death, and
3. pain and suffering of the injured persons, their families, and their friends.

They reported that injury due to falls yielded the second highest cost after motor-vehicle accidents, estimated at $US37.3 billion in 1985. Englander *et al.* [67] estimated the cost of falls in the elderly in the U.S.A. in 1994 to be $US20.2 billion, with a cost per injured person of $7,399. They predicted that the cost of falls would increase by 32.5% by 2020.

A study by Health Canada [9] found that fall injuries in Canada incur direct costs of \$2.4 billion and indirect costs of \$1.1 billion per annum. The study estimated that "targeting risk factors through prevention programs ... could lead to 7,500 fewer hospital stays and 1,800 fewer Canadians permanently disabled. The overall savings could amount to over \$138 million annually."

Although falls are referred to as accidents, the incidence of falls differs significantly from a Poisson distribution [71]. This implies that falls are not merely random events but are initiated by causal processes [147]. Much work has been done on the prevention of falls and there is good evidence that the risk of falls can be reduced and that some falls can be prevented.

The most successful approaches identify the risk factors for falls and then intervene to reduce those that are able to be modified.

Many risk factors for falls have been identified. Falls can be attributed to either extrinsic factors such as slippery floors or obstacles, or intrinsic factors such as neurodegenerative disorders, cardiovascular disease, parkinsonism, arthritis and the effects of medication [64, 133]. Over 85% of falls in the elderly are due to intrinsic factors that limit the ability to correct any imbalance when walking or transferring [133, 216]. Falling often appears to result from the accumulated effect of multiple specific disabilities [219]. This makes identifying the underlying causes of propensity to fall difficult, and different studies have found different factors to be important. Use of certain medications, cognitive impairment, disability of the lower extremities, impaired balance and gait, foot problems, a previous history of falling, poor mobility, advanced age, inactivity, frequent need for toileting, visual impairment, functional dependence, muscle weakness, poor reaction times, an unstable blood pressure response to upright tilt, illness, anxiety and depression are just some of the factors that have been found to contribute to the risk of falling [65, 97, 146, 148, 152, 180, 216].

Some fall risk factors can be reduced through appropriate interventions. Table 2.1 shows a list of fall risk factors compiled by Lord *et al.* [147] together with intervention strategies for those that are able to be modified. Strategies include education, exercise, environmental modification, clinical assessment and review, injury minimisation through appropriate clothing and technologies (for example, flat-soled footwear with good grip, hip protectors, walking aids, and personal alarm devices), and monitoring leading to early intervention to prevent falls [13, 147, 218].

Some evidence exists that interventions that target a single risk factor can reduce the number of falls [13], but strategies that target multiple risk factors appear to be more successful. In a randomised controlled trial (intervention group $n = 79$, control

Risk Factor	**Able to be modified?**	**Intervention strategies**
Advanced age	No	Discussion of increased risk
Female	No	Discussion of increased risk
Living alone	Possibly	Discussion of increased risk and possible change of living arrangements
Inactivity	Yes	Exercise, education
Limitations in the activities of daily living (ADL)	Yes	Exercise, motor training, use of aids, provision of assistance with ADL
History of falls	No	Discussion of increased risk
Medical factors	Possibly	Appropriate medical or surgical intevention
Medications	Possibly	Medication withdrawal, investigation of alternative strategies
Poor vision	Possibly	Use of appropriate spectacles, appropriate medical/surgical intervention, discussion of increased risk
Reduced peripheral sensation	No	Discussion of increased risk and compensatory strategies
Muscle weakness	Yes	Strength training
Poor reaction time	Yes	Exercise/training of fast, coordinated responses, e.g. exercise to music
Impaired balance	Yes	Exercise/training involving control of movements of centre of mass
Impaired gait	Yes	Exercise/training targeting causes, consider use of aids and appliances
Footwear	Yes	Advice re appropriate footwear
Environmental hazards	Yes	Installation of safety features, correction/removal of hazards

Table 2.1: Falls risk factors: ability to be modified and intervention strategies. Reproduced from Lord *et al.* [147]

group $n = 81$) Rubenstein *et al.* [191] found that a multifactorial intervention led to 26% fewer hospitalizations and a 52% reduction in hospital days over 2 years. Tinetti *et al.* [213] ran a randomised controlled trial (RCT) of multifactorial interventions (intervention group $n = 153$, control group $n = 148$) that led to 25% less falls and a reduction in fall risk factors in the intervention group. The multidisciplinary approach of Hornbrook *et al.* [103], tested in an RCT (intervention group $n = 1271$ households, control group $n = 1571$ households) led to a 0.85 reduction in the odds of falling and an actual falls reduction of 7%. Wagner *et al.* [228] randomly assigned 1559 seniors to an intervention group that implemented one-off interventions targeting fall risk factors ($n = 635$), an intervention group that received a general health promotion nurse visit ($n = 317$), and a control group that received usual care ($n = 607$). After 1 year the first group had a significantly lower incidence of falls than the control group. After two years, the differences between the groups narrowed, suggesting that continuing support is required to maintain a successful falls prevention programme. Close *et al.* [48] obtained a significant reduction in fall rate (intervention group, $n = 141$, 183 falls reported, control group, $n = 163$, 510 falls reported) over 1 year through a multifactorial intervention. The main drawback to studies of multifactorial interventions is that it is difficult to evaluate the different components used in these approaches and identify which components are actually necessary for a successful falls prevention strategy.

Day *et al.* [58] addressed this in a randomised controlled trial for falls prevention in the elderly ($n = 1090$). They tested 3 interventions, group based exercise, home hazard management, and vision improvement, by dividing the cohort into 8 groups defined by the presence or absence of each intervention. They found that group based exercise, which led to improved balance, was the best single intervention but the effects were further improved by the addition of home hazard management or reduced vision management, or both.

One of the most important parts of a fall prevention programme is identifying people who are at risk in order to intervene before a fall occurs. In a report to the Commonwealth Department of Health and Aged Care in 2000, the Australian National Ageing Research Institute recommended that this be one of the primary directions for future research [13].

There are a range of characteristics that have been identified as predictors of falls and a number of falls risk tests have been developed. Lord *et al.* [143, 146] developed a comprehensive assessment tool to identify risk of falling based on individual performance and compared to age-adjusted norms. This test includes eyesight, re-

Balance Manoeuvres	Gait Observations
Sitting balance	Initiation of gait
Rising from a chair	Step length
Immediate standing balance (first five seconds)	Step height
Prolonged standing balance	Step continuity
Withstanding nudge on chest	Step symmetry
Standing balance with eyes closed	Walking stance
Turning balance (360°)	Amount of trunk sway
Sitting down	Path deviation

Table 2.2: Balance and gait evaluations. Reproduced from Tinetti *et al.*[219]

action time, leg strength, proprioception, and balance. Tinetti *et al.* [219] identified mobility testing as the best single predictor of recurrent falling. The test that they developed consisted of asking the subject to carry out a number of tasks focussing on balance and gait, and a trained observer scoring each task. The tests are listed in table 2.2.

Change in physical performance is a strong predictor of falls and the onset of functional dependence in the activities of daily living. Gill *et al.* [84] assessed physical performance in 775 functionally independent subjects in two tests separated by a 12 month interval. They found strong correlation between change in physical performance and functional dependence. They suggest that change in physical performance could be useful in predicting future disability if measured over shorter intervals.

Changes in gait are also a useful predictor of falls. The nature of these changes is discussed in section 3.6. Measurement of postural sway when standing is another useful predictor of falls. Elderly fallers have significantly greater levels of postural sway than do elderly non-fallers [83, 143, 156].

2.3.5 Disability and Independence

Any loss of functional independence has a substantial impact on quality of life. A person who loses functional independence can no longer carry out their normal daily activities without assistance. This leads to reduced quality of life, social isolation, loss of confidence, loss of condition through reduced exercise and activity, and can necessitate a move to a nursing home.

Functional dependence can be precipitated by chronic disease, neurological disorder or an accident such as a fall. Many of the risk factors for future functional dependence are the same as the risk factors for falling. Reduced lower extremity function is highly predictive of future functional dependence in elderly people. In particular, the time taken to carry out activities is important [88, 122, 209]. Guralnik *et al.* [88] tested a cohort of 1122 functionally independent subjects. Each subject was required to complete a short battery of physical performance tests, including a timed 2.4 m walk at a normal pace, assessment of standing balance, and a timed test of five repetitions of rising from a chair and sitting down. Subjects with the worst performances were 4.2 to 4.9 times as likely to develop functional disability within the next four years than those with the best performances, and those with intermediate performance scores were 1.6 to 1.8 times as likely to develop disability than those with the best scores.

2.3.6 Measuring Health

Measures of health are used to assess the effect of interventions, and to identify changes that may be predictors of functional dependence or a fall injury. During the last decade, much work has been done developing techniques and methods for measuring health status according to the broader definition put forward by the World Health Organisation (refer to section 2.2.2). These instruments are generally questionnaires completed by either the patient or a carer. They measure a number of indicators of different aspects of health status. A standard scale is applied to the measurement of each variable, and they are then combined to give an overall total score which can be compared across individuals and for the same individual over time. The different health measurement instruments can be divided into four classes:

- those that measure physical well-being (e.g. Barthel Index [154], Katz scale [116, 117], Functional Independence Measure [91, 119];
- those that measure mental well-being (e.g. Mini Mental State Examination [77], Geriatric Depression Scale [244]);
- those that measure social well-being (e.g. Weissman's Social Adjustment Scale - Self report [232], Katz Adjustment Scales [115]); and
- those that measure overall health status and quality of life (e.g. Quality of Life Index [200], coop/wonca charts [177], Short Form 36 (SF-36) [229, 230], DUKE [183], Sickness Impact Profile [25], Nottingham Health Profile [104]).

Self-evaluation of health status is becoming an increasingly important tool for the measurement of health. Several studies have indicated that self-evaluation of present health status is a significant predictor of future mortality [107, 106, 114, 171]. Idler and Kasl [106] note that "subjective self-evaluation also conveys different information than more objective health ratings".

However, self-evaluation is intrinsically subjective and is heavily dependent on the subject's ability to recall events. This may lead to considerable discrepancy between the patient and clinician evaluation [138]. Moreover, self-evaluation appears only to be able to predict gross changes in health. Objective measures of health status, in particular, of functional status are needed to assess the affect of interventions on the patient's health and to accurately monitor changes in health status.

2.3.7 Measurements of Physical Well-Being

One of the primary measures of physical well being is the subject's ability to carry out routine daily activities. The assessment of physical activity in free-living subjects is central to a complete understanding of the relationship between daily physical activity and health. This is typically assessed in terms of functional ability, or functional status, which provides a measure of the patient's ability to carry out her or his routine daily activities. The World Organization of Family Doctors (WONCA) Classification and Research Committee defined functional status as "the level of actual performance or capacity to perform, both in the sense of self-care or being able to fulfil a task or role at a given moment or during a given period" [171].

Functional status provides an indicator of the ability of a person to live independently. Within the domain of routine daily activities, there are a number of specific abilities that are needed for functional independence. The most basic are called the activities of daily living (ADL) and the more complex activities are referred to as the instrumental activities of daily living (IADL). The ability or inability to perform ADLs and IADLs can be used as a very practical measure of ability/disability in many disorders.

The activities of daily living (ADLs) are those activities necessary for basic independent function. Katz [116, 117] defines these as bathing, dressing, toileting, transferring from bed to chair, continence, and feeding. Katz noticed that the loss of functional skills occurs in a particular order, the most complex functions being lost first. Empirically, the six activities included in the index were found to lie in a hierarchical order of this type - the ability to bathe independently is lost first, and the ability to feed independently is lost last. Other items, such as mobility, walking, or stair climbing, did not fit this pattern and were excluded from the list of ADLs

[116]. There have been some slight alterations made to this list by some authors and improvements to the way in which they are measured, but the basic list is still widely accepted as a reasonable definition of ADL.

The ADL scales are concerned with severe levels of disability and, while they are necessary to survival, more skills are required for independent living. The IADL scales extend the ADL to include activities that are normally undertaken by those living independently in the community. These include mobility, walking, stair climbing, shopping, cooking, and managing money. The ability to carry out IADLs is strongly correlated with functional independence in community-dwelling patients.

Measures of functional status and ability in ADLs and IADLs are normally assessed by asking the patient or a carer to complete a questionnaire, or to keep a diary, or by clinical assessment through a battery of specific tests that are assessed by a trained observer, or by the recording of quantitative parameters during a battery of tests [164]. All of these methods of measuring functional status can be time consuming for the patient, carer and specialist. Additionally, the first methods are subjective and rely on the patient or carer to remember events and performances. Observation by a trained person is also inherently subjective. The main limitations of assessment using a battery of tests is that the patient is usually assessed in an artificial setting, not actually performing the activities as part of the usual daily routine at home. Although these tests can provide a good indication of functional status, they cannot take into account every factor involved in carrying out the routine daily activities. Many factors such as lighting, floor surface, and choice of clothing can affect a subject's performance in daily activities. Moreover, the clinical tests can only provide a snapshot in time of functional status. Many of the factors that impinge on functional status are subject to variation. These include medication, the onset of illness, emotional health, and levels of fatigue. Such factors may vary over the course of days, and may even fluctuate during the day. A clinical assessment cannot measure these variations in and so may fail to detect important changes in functional status.

These limitations can be overcome by the provision of continuous, objective monitoring in the home environment. Veltink *et al.* [225] stated that "to improve the rehabilitation treatment of patients, their activities of daily living should be evaluated in their domestic environments. This evaluation can give a good indication of the activity restrictions the patients experience because of their disabilities. The rehabilitation treatment can then be directed toward relieving these activity restrictions." Continuous monitoring allows temporal fluctuations to be identified and measured. In order to be practical and not place unreasonable demands on the patient or an observer, such monitoring also needs to be automated and unobtrusive.

Monitoring of human movement is intrinsic to the measurement of functional status. Since functional status is a measure of a person's ability to carry out routine daily activities, it is necessary to measure the way in which the person carries out (or fails to carry out) these activities. It is also important to know how much activity the person is undertaking during the day, and at what level of intensity this activity is undertaken. Techniques for the quantitative assessment of human movement may provide a means of continuously and objectively monitoring a subject to identify changes in functional status and health.

2.4 Techniques for Assessing Human Movement

2.4.1 Introduction

Techniques for the quantitative assessment of human movement may provide a means of continuously and objectively monitoring a subject to identify changes in functional status and health. Many different techniques have been used to assess human movement in the clinic, the laboratory and in the home. The main approaches to the assessment of balance and human movement are described in the following sections.

2.4.2 Assessing Balance

The assessment of balance has traditionally been centred around global measures of balance abilities such as the measurement of total body sway or the measurement of postural reflex function [243].

Marsden and Thompson [159] list seven key elements that should be examined during any assessment of balance and gait. These are

1. The ability to rise from a chair,
2. The ability to stand unsupported,
3. The ability to withstand a push,
4. The ability to initiate walking,
5. The ability to locomote,

6. The ability to negotiate turns, and
7. The ability to walk a straight line heel to toe.

A number of procedures have been described to assess balance. The Fukuda stepping test was one of the earliest established tests of balance, assessing vestibular function. It required the subject to march in place with eyes closed for 45 s after which the position of the body is assessed relative to the starting population [112].

One of the simplest and most widely utilized procedures is the Romberg test [112]. In this the subject stands with feet together and eyes closed while being observed for increased postural sway. The Romberg test is very easy to administer but is inherently subjective. Variations on the Romberg test include the sharpened Romberg, in which the patient assumes a stance with feet heel-to-toe while being observed for increased sway or timed for total duration in position, the tandem stance in which the patient assumes a stance with feet overlapping, and narrow base of support while being observed for increased postural sway or timed for total duration in position, and the one-leg stance in which the subject stands unsupported on one leg while being timed for total duration in position or for 30 s, whichever comes first [112]. The one-leg stance provides a general measure of balance, but its reliability has not been established in large part due to the position of the non-weight bearing leg, and arms, and it is often not tolerated by elders or by individuals with neurologic impairment. The posture grid test provides a less subjective variation of the Romberg test. In this, the subject stands in front of a posture grid while the clinician observes the excursion of body sway (in degrees and distance) under different balance conditions, such as eyes open and eyes closed.

Other clinical tests that assess the integration of sensory information and balance are used with neurologic and geriatric patients. In a typical test, the subject attempts stands quietly for 30 s with (i) eyes open; (ii) eyes closed; and (iii) in the presence of visual conflict. The three tests are then repeated while the subject stands on a foam block. The aim of the test is to identify whether the subject is over- or under-dependent in use of the senses governing balance.

In another variation, the sway path generated by the subject is traced onto paper. The Hinsdale stylus technique, which is not widely used, uses a cap, which is worn by the subject, with a pencil attached. A sheet of graph paper is placed directly under the pencil and the path of the subject's sway is traced onto graph paper. The area and the complexity of the sway path are measured [196]. The Wright ataxiameter is a shoulder-mounted device with a pencil attached. It also traces out the sway path. A swaymeter that uses a pencil attached to the back of

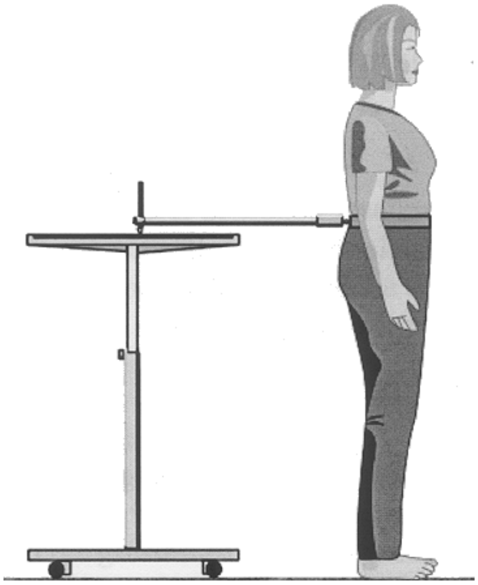


Figure 2.11: Sway can be measured using a swaymeter, which measures displacements of the body at waist level. The device consists of a 40 cm long rod with a vertically mounted pen at its end. The rod is attached to subjects by a firm belt and extends posteriorly. As subjects attempt to stand as still as possible, the pen records the sway of subjects on a sheet of millimetre graph paper fastened to the top of an adjustable height table. Reproduced from Lord [139].

a waist belt has also been used [144]. A setup for this apparatus is shown in figure 2.11.

Force plates have also been used to measure balance [243]. Subjects stand quietly on the force plate, and the excursion of the centre of pressure is calculated. This is used to infer the degree of stability. However, there are some methodological issues with using this type of centre-of-pressure approach to gauge stability. One problem is that changing the relationship of the body segments can alter the centre of pressure without affecting the stability of the subject. A second problem is that these measures do not necessarily correlate well with postural instability in daily life. For example, many patients with severe neurological deficits such as Parkinson's disease show normal sway in quiet stance [243].

Other approaches to assessing balance have looked at components of motor control [243]. The motor components have been studied by means of reactive and proactive balance control measurements. Reactive methods measure how well the subject responds to a disturbance. The subject is either asked to stand on a motion platform which is then moved, or is asked to stand on a compliant surface. In proactive methods subjects are asked to perform a lifting or pushing task while their balance is assessed. Proactive balance is also assessed by monitoring the subject's balance while walking.

2.4.3 Assessing Gait and Other Movement

Movement is most commonly assessed in the clinic or the gait laboratory, often using multiple techniques, including direct observation, video recording, photogrammetry, electromyography, force platform analysis and kinematic and kinetic techniques. The gait cycle of a subject is normally sufficiently regular that only several gait cycles need to be studied. The same is true for many other basic movements such as standing up out of a chair, where several repeated trials are sufficient to obtain a measure of the subject's functional ability in this task.

2.4.4 An Overview of Assessment Techniques

Observation Techniques

Observation techniques are still widely used for assessment of aspects of balance and human movement. A trained observer can rapidly and accurately classify a subject's movements as normal or otherwise simply by observing the movement.

Functional Tests

Functional tests are routinely used for assessing balance during movement. Validated functional tests provide formal assessment tools that use observation techniques to rapidly assess salient parameters. The performance of the subject is graded on an ordinal scale. Two examples of functional tests are the Timed Get-Up-and-Go Test [160, 186], and The Tinetti Balance and Mobility Scale [219]. In the Timed Get-Up-and-Go test subjects are required to stand up from a chair, walk 3 metres, turn around and walk back. This test has been found to be a good indicator of functional ability and correlates well with the Barthel Index for assessment of ADL. Normal subjects can finish the test in less than 10 s, subjects who are independent in ADL but may need some assistance in IADL can finish the test in less than 20 s, while subjects who are functionally dependent need at least 30 s to complete the test, if it is possible at all [243]. The Tinetti test was developed to screen for balance and mobility skills and to determine the risk of falls. This test was described in section 2.3.4. The tools for assessing physical activity that were mentioned in section 2.3.6 are other examples of functional tests.

Simple Timed Measures

Analysis of gait characteristics such as average walking speed, stride length and cadence can be computed by measuring the time taken by a subject to traverse a path of known length and counting the number of steps taken.

Video Recording

Video recording is used in two different ways. It is used to record the subject's movement so that analysis by observation can be checked and post-hoc analyses carried out. It is also used to provide a data stream to a motion analysis computer program for detailed quantitative motion analysis (photogrammetry).

Motion Analysis Laboratories

Motion analysis laboratories use a wide range of technologies including pressure sensors, accelerometers, force transducers and cameras to collect data on human movement. The data are normally processed on a personal computer. In most studies of human movement, the body is modeled as a series of linked rigid segments, in which the motion of one segment affects the motion of many others through biomechanical interactions and neurological integration [243]. Photogrammetry is routinely used in kinematic analysis in motion laboratories. Reflective markers are attached to the subject around the areas of interest. As the subject performs the movement under investigation, a video camera films the movement and the data are streamed to the personal computer where the movement of the reflective markers is tracked. The computer is equipped with a model of the human body and uses this model to translate the positional movement of the reflective markers into quantitative measurements of linear and angular displacement, velocity, acceleration and force.

Electromyography

Electromyography (EMG) is the measurement of the electrical activity of muscles during contraction. It is regularly used in motion analysis. Surface skin electrodes and intramuscular wire electrodes measure the electrical activity of muscles. The signals are then normally full wave rectified and low pass filtered. It has been found that the relationship between rectified-filtered EMG and muscle force is nonlinear, varies with muscle length (i.e. joint angle) and differs among muscles. The patterns of EMG activation during the gait cycle vary with velocity and from subject to subject, but the patterns of EMG activation vary very little for a given subject walking at a constant speed [243].

Force Plates and Pressure Sensors

Mechanical force platforms were introduced by Jules Amar in 1916 and further developed by Herbert Elftman in 1938 [110]. Mechanical force platforms are used to record the three components of the ground reaction force and their point of application. These data are used to compute dynamics of movement.

Fixed floor mounted pressure sensors and pressure insoles are used to study the distribution of pressure beneath the foot during gait.

Kinematics

Kinematics pertains to the motion of a body in space without regard to the forces that cause this motion. Any body segment moves in three-dimensional space with six degrees of freedom—three directions of translational motion and three of rotational motion. Goniometers are used to measure joint angles between body segments [82, 83]. Accelerometers are used to record the motion of body segments [18, 130, 227]. Gyroscopes have been used to measure the orientation of body segments [150].

Kinetics (Dynamics)

Kinetics is the study of forces. Normally, the investigator begins with a complete knowledge of rigid body motion (measured using the motion laboratory systems) and seeks to compute the underlying forces. Body segment parameters (moment of inertia, mass, centre of mass), kinematic analysis and measured ground reaction forces are used to compute the forces and torques at the joints between body segments.

Other sensors

Electromechanical switches can be used to determine precise event timing. For example, a switch or pressure sensor attached to the heel can be used to identify the exact timing of heelstrike in gait. These switches can be used in combination with other techniques to understand more about the movement [70].

Unobtrusive Sensor Monitoring

Unobtrusive monitoring refers to a technique in which the movement of the subject is monitored without the need for subject compliance [43, 85, 198]. The subject is monitored indirectly by means of sensors placed around the home, such as threshold detectors across doors, current sensors on electrical appliances and switches on drawers and cupboards. By monitoring the activity in these sensors a pattern of movement can be developed for the subject around the home. This approach bypasses the difficulties inherent in processing the signal from a motion camera, and avoids the privacy issues involved with collecting images of the subject at home, but can only provide limited information on gross parameters.

2.4.5 Summary

There are many different techniques available for assessment of balance and movement in the laboratory setting. However, most of these are inappropriate for use in unsupervised home monitoring. The photogrammetric techniques require a dedicated laboratory set up. The observational techniques and the functional assessment tools are generally too onerous and time consuming to be conducted on a regular basis. Moreover, they are only sensitive to gross changes in functional ability. Force platforms are very expensive and require a precision set up and specialised tests to be conducted under careful supervision in order to obtain useful data. Subjects cannot be engaged in their routine daily activities while force platform analysis is undertaken. Using a camera to photograph or film the subject generates large amounts of data that are difficult and time-consuming to process and taking photographs of the subject while they are at home raises concerns about subject privacy.

Sensors such as pressure sensors, electromechanical switches, accelerometers, goniometers and gyroscopes can be used in an unsupervised home setting. Systems can be designed to use these sensors in an ambulatory setting and they can be used to assess subject movement during routine daily activities. This “has the additional advantage that assessment of gait during normal daily life is probably more valid than gait analysis in a movement laboratory” [38]. Of these individual types of sensors, the accelerometer can provide the most information over the widest range of activities. Piezoresistive accelerometers provide measurement of vertical orientation (tilt angle), and body acceleration. As opposed to a switch that can only be in one of two states, they provide a range of measurement. They have been used to objectively monitor physical activity, posture and balance, parameters of gait, and to classify activities. Steele *et al.* [201] observed that “accelerometers have the advantage over other physical activity monitoring techniques in that they are capable of providing information on specific patterning of activity. They are able to measure an important dimension of functional status not previously well-described." Advances in the state of art technology have led to the development of miniaturised, lightweight, inexpensive accelerometer systems that can be worn for days or even weeks [31].

2.5 Chapter Conclusion

Demographic changes are leading to a situation in which the quality of care demanded by an ageing population can no longer be delivered due to increasing costs and increasing burden on hospitals and other care facilities.

The predominant causes of hospitalisation and institutionalisation are cardiovascular disease, neurological disorders, and injury due to falls. The cardiovascular diseases and the neurological disorders are (at present) degenerative, incurable conditions, and treatments consists of careful monitoring and management of the condition to prevent deterioration and to promote quality of life. Falls risk can be reduced through appropriate interventions once a fall risk factor has been identified. Identification of fall risk factors can be achieved through clinical testing and enhanced by regular home monitoring to detect changes to risk factors. Predictors of functional dependence can also be identified by observing longitudinal changes in characteristic movements.

Continuous home monitoring can provide an ongoing, objective measure of functional status. It can also be used to detect the occurrence of a fall. Accelerometry is a practical tool that shows promise in the area of continuous home monitoring. Applications of accelerometry to the assessment of human movement are discussed in the next chapter.

Chapter 3

Background Information

3.1 Overview

There is growing interest in the use of accelerometry for monitoring human movement in free-living subjects. The first section of this chapter reviews the types of commercially available accelerometers and the performance specifications that are required for the assessment of human movement.

Accelerometers are often attached at the waist. The advantage of this placement is that the centre of mass of the body is normally contained within the pelvis and so attachment at the waist allows monitoring of accelerations near the centre of mass. This is discussed in the second section.

The subsequent sections review current knowledge pertaining to balance, postural sway, the stand-sit-stand movement and walking. The use of accelerometry in assessment of these activities is reviewed.

The final sections of the chapter review the state of the art in the use of accelerometers for classification of human activities, estimation of metabolic energy expenditure and automatic detection of falls.

3.2 Accelerometry in the Assessment of Human Movement

3.2.1 Introduction

Human movement is generally assessed in the laboratory or clinic. Although laboratory techniques can provide highly accurate and valuable clinical information about motor activities, the results obtained can be significantly different to those obtained by monitoring in the natural home environment [123].

In the last few decades, technological advances have allowed the development of miniature, low cost accelerometers. This has led to interest in using accelerometry as a tool for assessment of human movement in the natural environment. Studies in which accelerometers have been applied to the assessment of human movement have almost universally indicated that they show promise as a tool for monitoring free-living subjects [31, 56, 70, 165, 19, 221, 173, 32, 195, 225, 162, 201, 72, 76, 99, 18, 46, 38, 40]. Accelerometers can provide objective, quantitative information on human movement. They are "capable of providing information on specific patterning of activity" and can "measure an important dimension of functional status not previously well-described" [201]. Their small size and relatively low cost also make them a convenient tool for monitoring free-living subjects.

3.2.2 Commercially Available Accelerometers

There are two basic types of commercially available accelerometers. These are the piezoelectric accelerometer and the piezoresistive accelerometer. Piezoelectric accelerometers are like damped mass spring systems in which a piezoelectric element acts as a spring and damper. An acceleration of the mass causes a stress in the piezo crystal. The crystal generates an electrical charge from which the acceleration can be measured.

Piezoresistive accelerometers use silicon resistors whose electrical resistance changes in response to an applied acceleration. The sensor is made from a surface micromachined polysilicon structure built on top of a silicon wafer. Polysilicon springs suspend the structure over the surface of the wafer and deflect with acceleration forces. There are several ways in which the acceleration can then be measured. For example, the resistors can be connected in a Wheatstone bridge configuration to produce a voltage proportional to the amplitude of the acceleration of the small mass in the sensor. Alternatively, a differential capacitor with central plates attached to the moving mass and fixed external plates can be used. An applied acceleration will unbalance the capacitor, resulting in an output wave with an amplitude proportional to the applied acceleration.

Piezoresistive accelerometers are smaller than piezoelectric accelerometers. Miniature piezoresistive accelerometers are now readily available and are relatively inexpensive. Piezoresistive accelerometers require an external power source whereas piezoelectric accelerometers do not. Piezoresistive accelerometers are sensitive to constant accelerations, such as the acceleration due to gravity, whereas piezoelectric accelerometers do not have a d.c. response. Piezoresistive accelerometers are traditionally used as tilt sensors while piezoelectric accelerometers have traditionally been used for applications such as vibration monitoring on machinery and turbomachine condition monitoring.

Recent human movement research has favoured piezoresistive accelerometers, even when a d.c. response is not required. This is because the d.c. response allows the calibration of the accelerometer by rotation within the gravitational field.

More recently, accelerometers based on thermal sensor technology have become commercially available [187], although they have not yet, to the knowledge of the author, been used for monitoring human movement. In these instruments, thermocouples are placed around a heating element to act like a Wheatstone bridge, where any difference in temperature between sensing elements results in a differential signal that is suitably amplified and conditioned. A change in acceleration results in a change in temperature gradient, and hence a change in output signal. Functionally, thermal accelerometers are very similar to piezoresistive accelerometers. They require an external power supply and can measure constant accelerations as well as changing accelerations. However, this technology can measure accelerations with greater resolution for lower cost than other technologies.

3.2.3 Accelerometer Specifications for Human Movement Monitoring

Most of the frequencies and amplitudes of human movement are quite low. Accelerometers for monitoring human movement need to be designed to measure small magnitude changes at low frequencies.

Bhattacarya *et al.* [26] studied the vertical accelerations generated during running and trampoline jumping. They found that those generated during running were greater than those generated during trampoline jumping. The accelerations recorded at the ankle ranged from 3.0 to 12.0 g, from 0.9 to 5.0 g at the low back, and from 0.8 to 4.0 g at the head. Cappozzo [41] reported that, during walking, vertical accelerations ranged from -0.3 to 0.8 g and that horizontal accelerations ranged from -0.3 to 0.4 g at the low back and from -0.2 to 0.2 g at the head. Here g refers to the acceleration due to gravity, approximately 9.81 m.s^{-2}.

During running, most acceleration is below 18 Hz at the ankle, and occurs at lower frequencies at the low back and head. During trampoline jumping, the frequency content was found to be similar at all three sites and ranged from 0.7 to 4 Hz [26]. During walking, most of the acceleration power in the upper body occurs at frequencies below 5 Hz [41]. Antonsson and Mann [21] reported that 98% of the power in barefoot walking is contained below 10 Hz and 99% is contained below 15 Hz. Aminian *et al.* [20] found that there was no significant acceleration frequency component above 16 Hz at either the low back or the heel during treadmill walking. Sun and Hill found that the major energy band for daily activities was $0.3 - 3.5$ Hz [202].

In the light of these findings, Bouten *et al.* [31] concluded that in order to assess daily physical activity, accelerometers must be able to measure accelerations up to ± 12 g in general, and up to ± 6 g if they are attached at waist level. They must also be able to measure frequencies between 0 and 20 Hz.

3.3 Centre of Mass and the Pelvis

The centre of mass is a point equivalent of the total body mass for a rigid body. Newton's second law of motion for a mass system states that the resultant of the external forces on any system of mass equals the total mass of the system times the acceleration of the centre of mass. Thus, in order to determine "whole body" movement of a rigid body, it is sufficient to know the movement of the centre of mass.

The vertical projection of the centre of mass onto the ground is called the centre of gravity.

The position of the centre of mass of a human subject depends on the posture of the subject, but most of the time the centre of mass is located within the pelvis.

The pelvis is formed from three groups of bones: the sacrum, the coccyx and the two innominate bones (figure 3.1). The sacrum consists of the five sacral vertebrae, fused together. The coccyx is the vestigial tail made of three to five rudimentary vertebrae. The innominate bone on each side is formed by the fusion of three bones: the ilium, ischium and pubis. The only real movement between the bones of the pelvis occurs at the sacroiliac joint, and this movement is generally very small. It

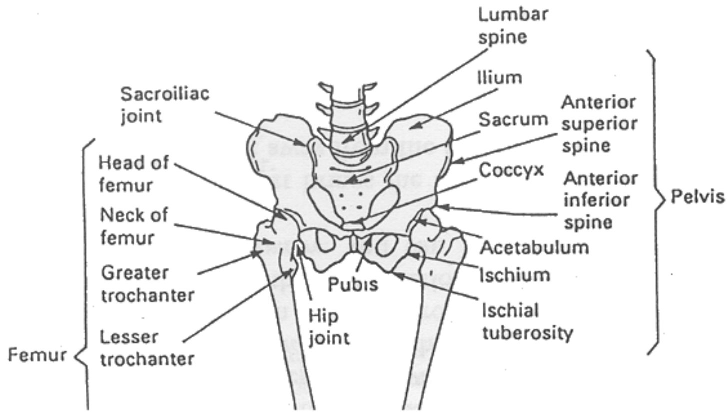


Figure 3.1: Bones and joints of the lower limbs. Reproduced from Whittle [235].

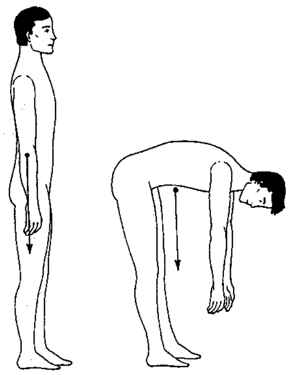


Figure 3.2: Centre of gravity when standing and bending. Reproduced from Whittle [235].

is thus reasonable to regard the pelvis as a single rigid structure [235].

When a subject is standing upright, the centre of gravity is just in front of the lumbosacral junction, in the middle of the pelvis [235]. Any movement of the body will cause the centre of mass to shift. It is entirely possible for the centre of mass to move outside the body. For example, the centre of mass of a person bending down to touch their toes is typically in front of the top of the thigh (figure 3.2). However, for most basic movements and postural orientations, the centre of mass remains within the region of the pelvis.

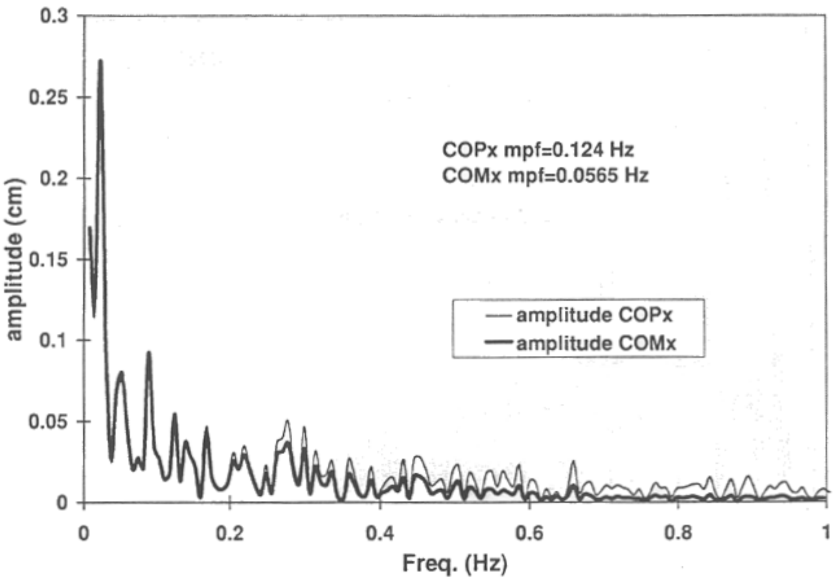


Figure 3.3: Fourier transform of Centre of Pressure (COPx) and Centre of Mass (COMx) in the anteroposterior direction. Reproduced from Winter [240].

3.4 Standing and Postural Stability

Postural stability is the ability of an individual to maintain the position of the body, or more specifically, the centre of mass, within specific boundaries of space without needing to move the base of support. This requires the complex integration of sensory information regarding the position of the body relative to the surroundings, and the ability to generate forces to control body movement [147]. During quiet standing, balance is constantly being corrected to keep the body upright, and this is characterised by small amounts of postural sway [147]. Impaired balance and impaired postural control both lead to a high risk of falling [216, 214, 213, 219].

The body sways about the ankle joints in the antero-posterior direction with an undamped natural frequency of around 0.3 Hz for a normal adult, although muscle and joint damping reduce this frequency [240]. Figure 3.3 shows the Fourier transform (FFT) of the antero-posterior postural sway of the centre of mass for a typical adult subject.

Above thirty years of age postural sway tends to increase with increasing age. This is caused by a range of factors, including reduced lower extremity muscle strength, reduced peripheral sensation, poor near visual acuity and slowed reaction time [66, 144]. Increased sway is particularly evident in studies in which subjects stand with their eyes closed [147]. In older people postural sway, particularly when standing with eyes closed, is a predictor of future falls [143, 156, 75].

Both amplitude and frequency are important in assessment of postural sway, with large sway amplitudes and higher frequencies being indicative of postural instability [112, 75]. It has been postulated that the harmonic content of the postural sway signal contains information regarding the degeneration of the balance control system due to ageing and balance related pathologies [240]. The spectral pattern of sway obtained using a force platform has been found to be useful in distinguishing between various pathological conditions, and it has been suggested that "quantitative sway assessment may be most important in the identification of subtle and idiopathic falling disorders" [112].

Different approaches to measuring balance and postural sway were described in section 2.4.2. These included the Romberg test, the Wright ataxiometer and force platform analysis.

All of these tests need to be set up and conducted by an observer, not by the patient him or herself. None of these tests are suitable for assessment of balance during routine daily activities, nor for continuous monitoring. Moreover, the Romberg-style tests are subjective and can only provide a qualitative assessment, and force platform analysis and ataxiometric tests can only provide a measure of static postural sway, which may not reflect the likelihood of falls and instability in daily living.

Accelerometry has been found to be a reliable method for measurement of balance during standing and walking, with a high absolute test-retest reliability [169]. Kamen *et al.* [112] used an accelerometer to quantitatively assess sway frequency and amplitude. Twenty subjects, ten young (18–32 years) and ten old (69–86 years), were asked to stand (i) normally on a firm surface; (ii) on a block of foam; and (iii) on a block of foam with eyes closed while sway along the anterior-posterior axis was measured using a uniaxial accelerometer. They analysed data obtained from accelerometers attached at the shoulder, knee, back, and forehead. The most consistent results were obtained when the accelerometer was positioned on the subject's back, midway between the posterior superior iliac spines at about $S2$ (the second sacral vertebra). They also suggested that a wearable accelerometer could be used to provide a clinician with some indication of the number of "destabilizing challenges" faced by a person during a normal day.

In a preliminary study with eight subjects, Mayagoita *et al.* [163] found that measurements from a sacrum mounted triaxial accelerometer (TA) were able to distinguish between four different test conditions—(i) feet apart, eyes open; (ii) feet apart, eyes closed; (iii) feet together, eyes open; and (iv) feet together, eyes closed—

as well as or better than simultaneous force platform measurements. Waarsing *et al.* [227] defined a performance parameter based on the balancing forces during walking as reflected in the power spectrum of the signal from a TA. Preliminary work found that the performance parameter could be used to order different gait patterns in terms of relative stability.

3.5 The Sit—Stand—Sit Movement

The ability to rise from a chair is of fundamental importance for functional independence. Rising from a chair is regarded as the most mechanically demanding functional task undertaken during daily activities [122], and is a prerequisite for gait [128]. An inability to rise from a chair can prevent an otherwise functionally independent subject from independent living [172]. The ability to sit down in a controlled manner is of equal importance.

Standing and sitting are movements that depend heavily on balance and leg strength to support and control the movement. Both movements have been shown to follow a structured sequence of events [122, 121]. Figure 3.4 shows the linear displacement of the trunk and the angular displacement of the knee during sit-to-stand and stand-to-sit transitions for a normal subject.

There are four basic components to each of the sit-to-stand and the stand-to-sit transitions. These components are listed in table 3.1. The forward lean of the rising phase serves as a means of developing forward momentum in the horizontal direction. The knee movement changes the direction of motion from horizontal to vertical and assists in maintaining balance.

The timing between the forward lean, the knee extension and the vertical displacement component is critical to ensuring a change in direction and the preservation of equilibrium [42]. The timing of the knee extension is highly correlated with the initiation of vertical displacement. Kerr *et al.* [122] found that female subjects demonstrated a later initiation of knee extension than male subjects. The reason for this was not known, but it was suggested that differences in anthropomorphic variables and the relative position of the centre of gravity may be contributing factors. They also found that the knee extension phase occurred progressively earlier with age.

The total rise time for normal subjects is 1–3 s [122, 121] but can take up to 10 s for subjects with disability [172]. (Kralj *et al.* [128] reported mean rise times of 2.58–5.12 s for normal subjects, but these times are considerably greater than those quoted in other studies.) There is some evidence that rise times increase with

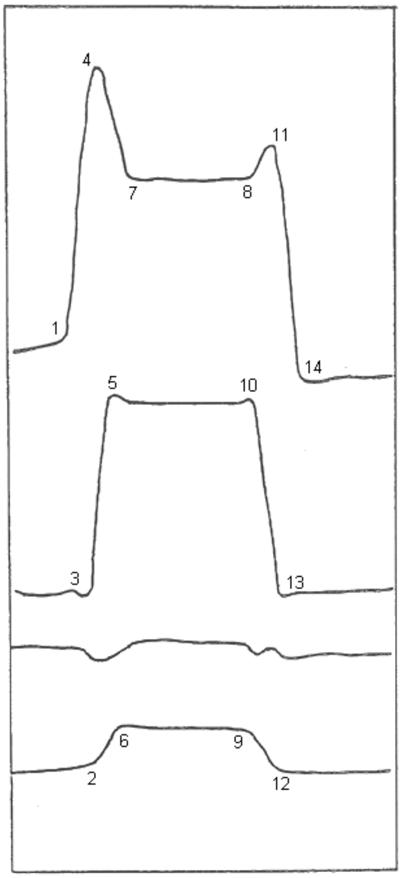


Figure 3.4: Analogue representation of the sit-stand-sit movement. The top three graphs represent linear trunk displacement in three dimensions and the fourth graph represents angular displacement of the knee in the sagittal plane. Rising Phase: 1. Initiation of forward lean, 2. Initaion of knee extension, 3. Initiation of vertical displacement, 4. Final forward lean, 5. Final vertical displacement, 6. Final knee extension, 7. Final backward lean (recovery). Descending phase: 8. Initiation of forward lean, 9. Initiation of knee flextion, 10. Initiation of vertical displacement, 11. Final forward lean, 12. Final knee flexion, 13. Final vertical displacement, 14. Final backward lean (recovery). Reproduced from Kerr *et al.* [122].

Component	Description	Boundaries
	Rising Phase	
Forward lean	Forward movement of the trunk	Initiation of forward lean/ final forward lean
Knee angular displacement	Extension of the knee	Initiation of knee extension/ final knee extension
Vertical displacement	Upward movement of the trunk	Initiation of vertical displacement/ final vertical displacement
Recovery	Backward movement of the trunk (stabilization)	Final forward lean/ final backward lean
	Descending Phase	
Forward lean	Forward movement of the trunk	Initiation of forward lean/ final forward lean
Knee angular displacement	Flexion of the knee	Initiation of knee flexion/ final knee flexion
Vertical displacement	Downward movement of the trunk	Initiation of vertical displacement/ final vertical displacement
Recovery	Backward movement of the trunk (stabilization)	Final forward lean/ final backward lean

Table 3.1: Components of the sit-stand-sit movements. Reproduced from Kerr *et al.* [122].

increasing age [122].

During the descending phase, the forward lean component has a significantly lower velocity than during the rising phase. The purpose of the forward lean during a descent is to position the centre of gravity over the base of support. Similarly to the rising phase, the timing between the forward lean, the knee flexion and the vertical displacement is critical. In particular, the end of the knee flexion and the end of the vertical displacement are closely related.

The total time to descend was around 2 s for normal subjects and was less age dependent than the rise times [122, 121]. (Again, Kralj *et al.* reported significantly greater descent times of 4.01 to 5.38 s for normal subjects.)

The sit-to-stand and stand-to-sit movements have been generally assumed to have bilateral symmetry in normal subjects, although Lundin *et al.* [151] tested the validity of this assumption for lower extremity joint moment and found that left hip movement was significantly different from right hip movement in both groups. However, although the asymmetry was statistically significant, the magnitude of the asymmetry was small and may have only slight biomechanical significance.

Performance of the sit-to-stand movement changes with age. In elderly subjects the forward lean component moves gradually from a momentum generating function

Acceleration peak	Mean (ms)	SE	Range
Vertical acceleration, rising (va1)	795.6	6.5	759–819.5
Sagittal acceleration, rising (sa1)	798.8	6.3	763.3–819.5
Vertical acceleration, descending (va2)	1537.6	6.4	1500.0–1560.5
Sagittal acceleration, descending (sa2)	1551.0	6.3	1513.0–1572.5

Table 3.2: Temporal position of the major peaks of vertical and sagittal acceleration during the sit-stand-sit movement cycle. Reproduced from Kerr *et al.* [121].

to one in which the centre of mass is always positioned over the changing base of support [122]. The duration of the forward lean is increased and overlap with the vertical displacement component is decreased. This leads to a loss of integration between the components and places a greater demand on the lower limbs to provide the force for rising. However, the elderly have significantly reduced leg power. Bosco and Komi [30] found that those over 72 years of age retained only $20 - 25\%$ of the lower limb power found in young adults. This is believed to be the reason why some otherwise healthy elders have difficulty rising from a chair [122].

Although most published work on the sit-to-stand and stand-to-sit transitions has reported results in terms of displacement, Kerr *et al.* included acceleration-based results in their studies. They presented the temporal position of the major peaks of vertical and sagittal acceleration during the sit-stand-sit movement cycle, using data taken from 10 normal female subjects [121]. The accelerations are illustrated in figure 3.5 and the timing results are reproduced in table 3.2. They found strong correlations of $r = 0.907$ ($P < 0.0005$) between the time of the vertical acceleration peak and the initiation of knee extension in rising, and correlations of $r = 0.887$ and $r = 0.994$ ($P < 0.0005$) between the timing of the sagittal and vertical acceleration peaks in rising and descending, respectively. These results were supported by data from a later study of the sit-stand-sit movement in 50 normal subjects [122]. In addition, they reported a high correlation between the sagittal acceleration peak and the time of maximal forward lean during both rising and descent. In the case of descent, the time of the peak vertical acceleration occurred at the end of the vertical displacement at the time of regaining contact with the seat for young females and the elderly. For young men and the middle-aged, the peak occurred at the initiation of descent. They suggest that this variation is probably a reflection of the controlled nature of the eccentric muscle activity during this phase.

There may also be a relationship between timing of the peak accelerations and the risk of falling. Troy *et al.* [220] tested this hypothesis, using accelerometers, in a study of 37 elderly subjects—20 healthy and 17 with Parkinson's disease. An ac-

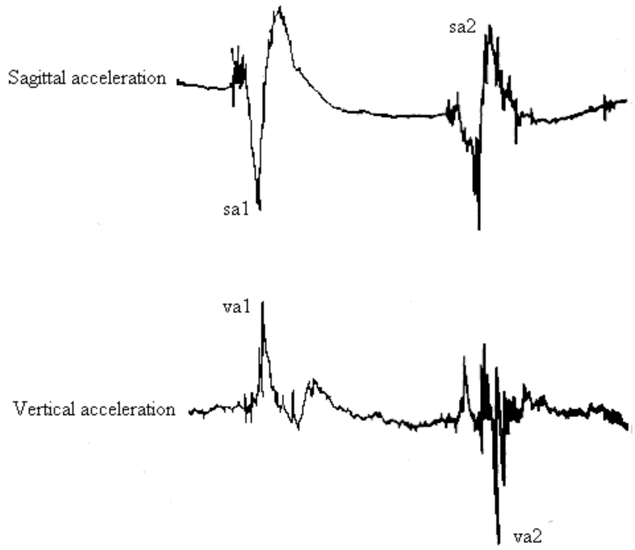


Figure 3.5: Graphical representation of acceleration during the sit-stand-sit movement cycle. Refer to table 3.2 for descriptors. Reproduced from Kerr *et al.* [121].

celerometer was attached to the waist of the subject who performed four sit-to-stand transitions. The timing between the acceleration maximum and minimum was compared a fall risk index that was derived from self-reported falls history. There was a moderate correlation ($r = 0.537$) between the sit-to-stand accelerometry characteristics and falls risk in the subject cohort, which suggests that the characteristics of the acceleration signal during sit-to-stand may be a useful predictor of falls in the elderly.

3.6 Walking

3.6.1 Introduction

Walking is a complex action that requires the integration of movement from many body segments. It is important for independent living and changes to a person's gait pattern can be early indicators of decline in functional ability or of future falls.

3.6.2 The Gait Cycle

Every person has their own individual style of walking that is designed to optimise the efficiency of the movement for that person [108]. Walking style is affected by many factors, such as physique, purpose of the walk, type of footwear, physical health and emotional state. Nevertheless there is a basic sequence of events that must occur for walking to be achieved: each foot in turn must leave the ground and then strike the ground again. This occurs in a regular sequence known as the gait cycle. One gait cycle is understood to go from initial foot strike to the next foot strike of the same foot. It is generally assumed that all successions of the gait cycle are identical. Although this is not strictly true, it is a reasonable approximation for walking at a constant speed [108].

The gait cycle consists of a stance phase and a swing phase, within which seven main events occur:

1. initial contact (heel strike),
2. opposite toe off,
3. heel rise,
4. opposite initial contact (heel strike),
5. toe off,
6. feet adjacent,
7. tibia vertical,
8. (initial contact).

These are illustrated in figure 3.6. Each component of the gait cycle is denoted as occurring at a certain percentage of completion of the gait cycle. This provides an indication of event sequencing but is not a indicator of the absolute timing. There is

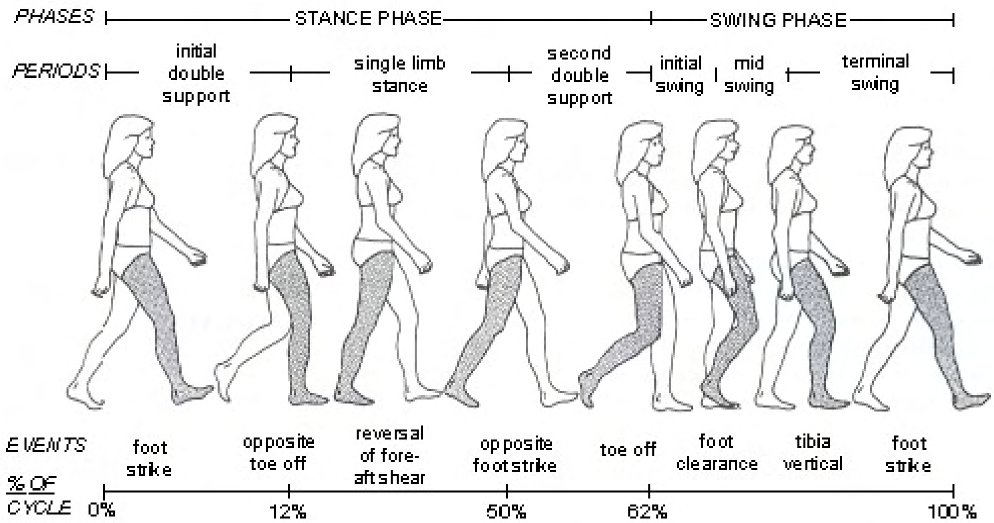


Figure 3.6: Typical normal walk cycle illustrating the events of gait. Reproduced from Sutherland *et al.* [203].

wide variation in the timing within the gait cycle between subjects, but the sequence of events is consistent across subjects [203]. The components of the gait cycle have been studied in detail and are well understood [35, 100, 175, 176, 203, 235].

In normal walking, the upper body moves forwards throughout the gait cycle, but with non-uniform progression. Its speed is fastest during the double support phases and slowest in the middle of the stance and swing phases. The whole trunk rises and falls twice during the cycle, through a total range of 40–50 mm [174, 184] in a normal adult, being lowest during double support and highest in the middle of the stance and swing phases. The trunk also moves from side to side, once in each cycle, with the trunk being over each leg during the stance phase. The total range of lateral trunk movement is 40–50 mm [184, 203] in normal adults.

The pelvis rotates 4–5° to either side in the transverse plane [108, 174, 209]. It also tilts 2° in either direction in the sagittal plane [174, 209], and in the frontal plane it lists downward about 5° on the side opposite the weight-bearing limb [108, 209].

In order to allow clearance for the limb to swing forward the knee joint of the non-weight-bearing limb flexes during the swing phase. The knee joint of the supporting leg is nearly at full extension as the other leg strikes the ground. As the body passes over the new supporting limb, the knee joint of the non-supporting limb flexes (approximately 15° [108]) and then extends again until the foot is place flat on the ground when the knee joint reaches full extension.

At moderate walking speeds transverse rotations of the thigh and shank occur in phase with the pelvic rotation. The angular displacements increase from the pelvis to the shank so that the shank transversally rotates approximately three times as much as the pelvis, although the exact nature of these rotations is highly individualistic.

The rotations of the upper body change with increasing walking speed [194, 222]. Below a speed of about $0.75\,\mathrm{ms}^{-1}$, the transverse thoracic rotations are in phase with the pelvic rotations. Above this speed, transverse rotations of the thorax and shoulders occur at $180°$ out of phase with the pelvic rotation, and the frequency ratio between upper and lower limbs changes from $2:1$ to $1:1$. Murray found average total excursions of $7°$ for the thorax and $9°$ for the pelvis in adult males walking at free speed [175], and similar values were found for adult females walking at free speed in low heel shoes [176]. Upper body rotation produces the arm swing characteristic of walking. The opposing lower body rotations provide a balancing effect that smooths the forward progression of the body as a whole. The ankle and foot also rotate during walking. Figure 3.7 shows the movement of body components of a subject during free walking in the sagittal plane, where the largest movements occur during walking [235]. The most significant accelerations also occur in this plane during walking, with the greatest accelerations being generated along the vertical axis [31].

It was stated earlier that each walking style is chosen so as to minimise the metabolic energy demand. For efficient walking, it is essential that the centre of mass moves smoothly. The pelvic rotation, pelvic list and knee flexion during early stance phase all act to smooth the path along which the centre of mass travels. These, together with additional movements of the knees, ankles and feet, result in the centre of mass following a sinusoidal displacement path, as shown in figure3.8.

The basic walking pattern is the same for males and females. However, Murray [176] reported that the amplitudes of many of the movement patterns in free walking are less for women than for men. Women were found to have smaller hip excursions, less transverse pelvic rotation, leading to shorter step and stride lengths and resulting in slower walking speeds. They also showed less motion of the head and upper limbs and smaller knee rotations than men.

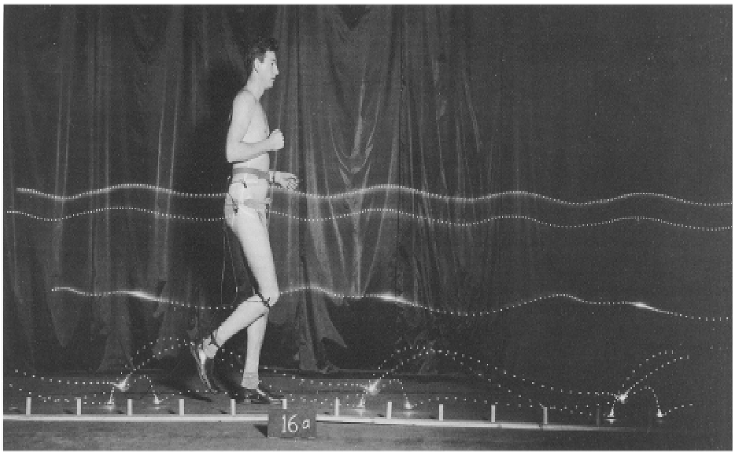


Figure 3.7: Interrupted light studies. The photograph was obtained by having a subject walk in front of the open lens of a camera while carrying small light bulbs located at the hip, knee, ankle, and foot. A slotted disc was rotated in front of the camera producing a series of white dots at equal time intervals. Note that the curve of displacement at the hip is a smooth curve but is not sinusoidal. This is due to the differences in phase of the two legs. Reproduced from Inman *et al.* [108].

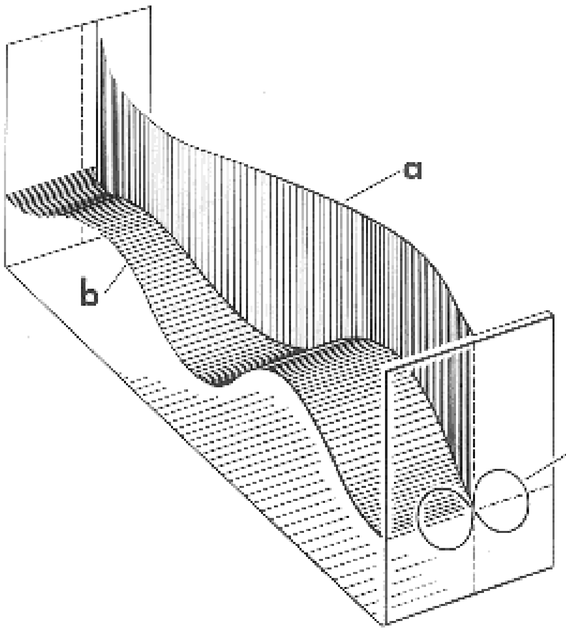


Figure 3.8: Displacements of centre of mass in three planes of space during a single stride (cycle). The actual displacements have been greatly exaggerated. (a) Lateral displacement in a horizontal plane; (b) vertical displacement. Combined displacements of (a) and (b) as projected onto a plane perpendicular to the plane of progression are shown in (c). Reproduced from Inman *et al.* [108].

3.6.3 Parameters of Gait

Five main linear parameters measure the average timing, linear displacement and velocity of progression. The *cadence* is defined to be the number of steps divided by the time taken (steps/min.). Thus, the cadence is a measure of half gait cycles.

The *cycle time*, or *stride time* is the time taken to complete one gait cycle.

$$\textit{cycle time}\ (\mathrm{s}) = \frac{120}{\textit{cadence}\ (\mathrm{steps.\,min^{-1}})} \tag{3.1}$$

.

Step length is the distance between the two heels during double limb support.

Stride length is the distance travelled between two successive foot strikes of the same foot.

Step width, also known as *stride width* or *walking base*, is the side-to-side distance between the line of the two feet, usually measured at the mid-point of the heel.

Walking speed is the average speed attained after approximately three steps.

$$\begin{aligned}\textit{walking speed}\ (\mathrm{m.\,s^{-1}}) &= \frac{\textit{stride length}\ (\mathrm{m}) \times \textit{cadence}\ (\mathrm{steps.\,min^{-1}})}{120} \\ &= \frac{\textit{stride length}\ (\mathrm{m})}{\textit{cycle time}\ (\mathrm{s})} \end{aligned} \tag{3.2}$$

The walking cadence for normal subjects is approximately 115–150 $\mathrm{steps.\,min^{-1}}$ [56, 70, 175, 176]. Guimaraes [87] found that the frail elderly had an average walking cadence of around 95 $\mathrm{steps.\,min^{-1}}$.

3.6.4 Modelling the Gait Cycle

Sophisticated mathematical models of walking are available. These models have been developed using high-quality three-dimensional data on the kinetics and kinematics of walking and are routinely used in gait laboratories. In a typical use of these models, a subject will walk with reflective dots attached to the points of interest on the body. The movement will be filmed. The movement of the reflective dots will be processed by the computer, which will use the generic gait model to form a complete model of the movement of that subject. These models are based on experimental data and use displacement as the basic parameter of movement.

Inman *et al.* [108] developed a simple model of gait that explained the displacement pattern of each part of the body in terms of the contribution of the pelvis, hip, knee and foot.

Simple models approximating movement during the gait cycle are still routinely used in analysis. In such a model, each of the six degrees of freedom are decoupled and analysed separately [81]. The axial movements of the trunk in normal walking are cyclical, roughly sinusoidal. There is a lateral oscillation with a fundamental frequency equal to that of the walking cycle, a vertical oscillation at twice the walking cycle frequency, and an oscillation along the line of motion, also at a frequency of twice the walking cycle and superimposed upon the mean forward velocity. Moreover, the three symmetric oscillations have a consistent phase relationship [53].

All of the parameters of pelvic translational and rotational displacement given earlier were for moderate walking speeds in adults. These parameters change with changing walking speeds. Typically, rotational displacements reduce with decreasing walking speed [209].

Gard *et al.* [81] developed a simple model to study displacement in the frontal plane (vertical and lateral directions) during gait. The simulation modelled the fundamental translational and rotational pelvic movements observed in normal walking using a simple rigid-body representation. They showed that their model provided a good representation of pelvic displacement when projected onto the frontal plane. Pelvic list and tilt were neglected in the model because their effect on the lateral displacement is small compared to the effect of pelvic rotation. The simple rigid body, shown in figure 3.9, had horizontal (x) and vertical (y) displacements given by

$$x = x_{\mathrm{max}} \cos(\omega t + \phi), \tag{3.3}$$

$$y = y_{\mathrm{max}} \cos(2\omega t), \tag{3.4}$$

$$\theta = \theta_{\mathrm{max}} \sin(\omega t), \tag{3.5}$$

where

$$\begin{aligned} x_{\mathrm{max}} &= y_{\mathrm{max}} = 2.0\,\mathrm{cm}, \\ \omega &= 2\pi\ [\text{stride frequency (Hz)}], \\ \theta_{\mathrm{max}} &= 5^\circ. \end{aligned}$$

The movements of points on the anterior (point A on Figure 3.9) and posterior of the pelvis (point C), and the centre of mass (point B) were simulated and compared to experimentally derived movements. The results obtained were similar in form to the experimental results, and are shown in figure 3.10.

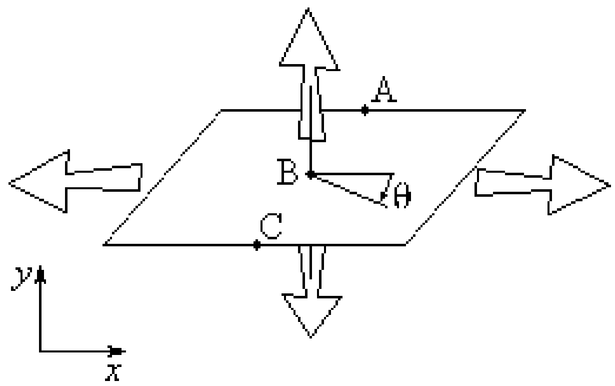


Figure 3.9: Idealised model of pelvic displacement during gait. A simple planar element has sinusoidal vertical and horizontal displacements and a sinusoindal rotation about a vertical axis passing through the centre of the element. Adapted from Gard *et al.* [81].

Crowe *et al.* [53] developed a model of gait with constant speed as

$$m\ddot{z} = F_z(t) - BW = \frac{a_{z0}}{2} + \sum_{n=1}^{\infty} A_{zn} \sin\left(\frac{2n\pi t}{T} + \phi_{zn}\right) - BW \tag{3.6}$$

$$m\ddot{y} = F_y(t) \tag{3.7}$$

$$m\ddot{x} = F_x(t) - kV = \frac{a_{x0}}{2} + \sum_{n=1}^{\infty} A_{xn} \sin\left(\frac{2n\pi t}{T} + G\phi_{xn}\right) - kV \tag{3.8}$$

where m is the body mass, $\ddot{z}$ is the vertical acceleration, $\ddot{y}$ is the lateral acceleration, $\ddot{x}$ is the forward acceleration, $F_z(t)$, $F_y(t)$, $F_z(t)$ are the vertical, lateral and forward ground reaction forces, k is a constant, V is the velocity of the forward motion, and BW is the body weight. The cyclical ground reaction force terms can be expanded as Fourier series with fundamental frequency $\frac{1}{T}$, where T is the gait period. This leads to the following terms describing the cyclical motion:

$$z(t) = -\frac{1}{m}\left(\frac{T}{2\pi}\right)^2 \sum_{n=1}^{\infty} \frac{1}{n^2} A_{zn} \sin\left(\frac{2n\pi t}{T} + \phi_{zn}\right) \tag{3.9}$$

$$y(t) = -\frac{1}{m}\left(\frac{T}{2\pi}\right)^2 \sum_{n=1}^{\infty} \frac{1}{n^2} A_{yn} \sin\left(\frac{2n\pi t}{T} + \phi_{yn}\right) \tag{3.10}$$

$$x(t) = -\frac{1}{m}\left(\frac{T}{2\pi}\right)^2 \sum_{n=1}^{\infty} \frac{1}{n^2} A_{xn} \sin\left(\frac{2n\pi t}{T} + \phi_{xn}\right) \tag{3.11}$$

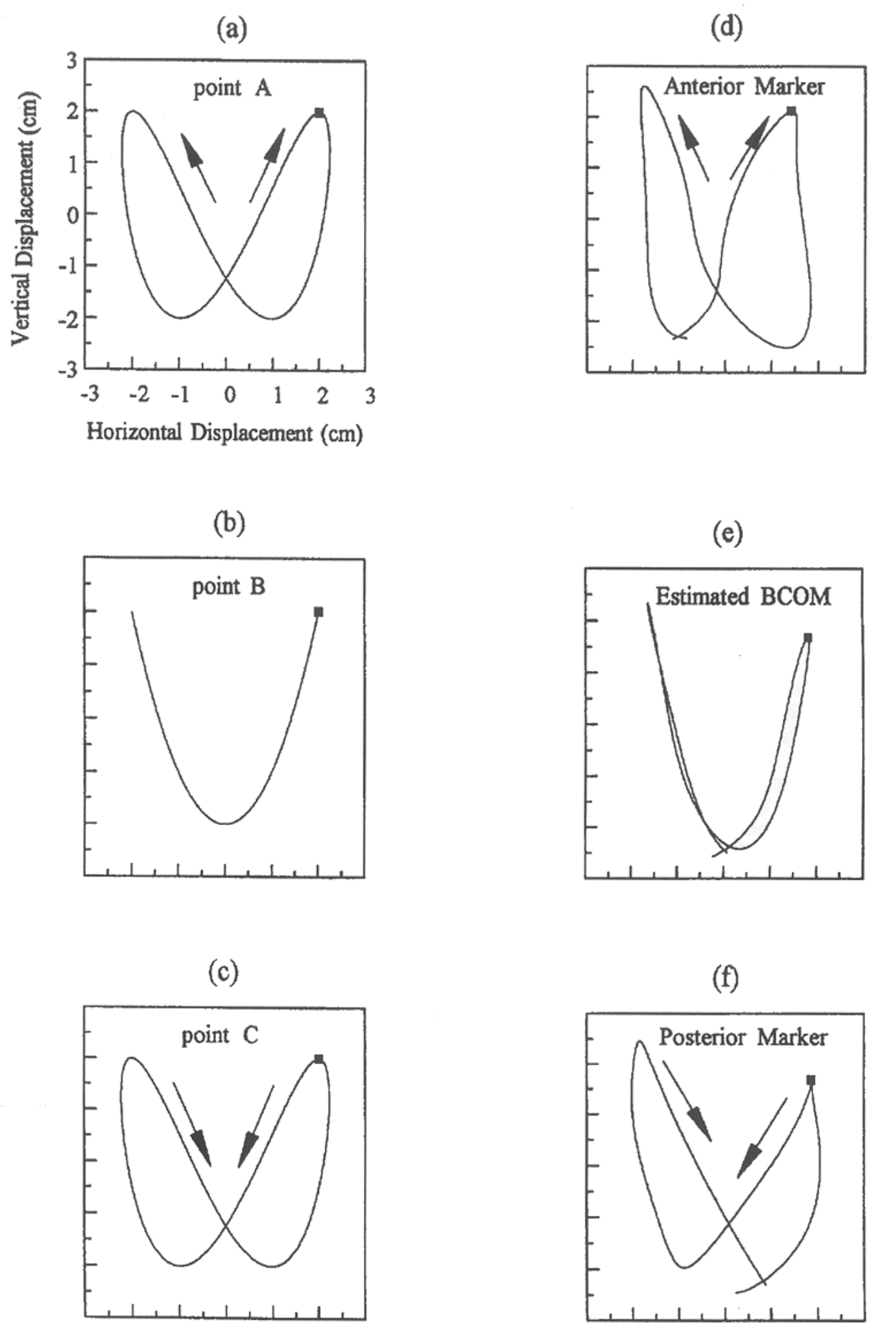


Figure 3.10: Lissajous plots for the modelled and experimental walking data. Rotation about point B causes phase shifts of the horizontal sinusoids for points A and C in the model, producing characteristic patterns observed in normal gait: (a)–(c) are plots for points A, B and C, respectively. The black squares indicate $t = 0$. Plots of the experimental data, (d) an anterior pelvic marker, (f) a posterior pelvic marker, and (e) calculated displacement of the approximated centre of mass within the pelvis, are similar to plots from the model. The black square occurs at mid-stance on the left leg; the arrows indicate the direction of forward time progression. Reproduced from Gard *et al.* [81].

where A_{xn}, A_{yn} and A_{zn} are the nth Fourier coefficients.

They found that good approximations to the body centre of mass oscillations were obtained from these equations using only the first and second order Fourier coefficients.

3.6.5 Variability as a Predictor of Gait Impairment

As people age, their gait pattern changes. Older people tend to have a shorter step length and spend longer in the double support phase of the walking cycle [89, 175, 176, 241]. As a result, older people walk more slowly than younger adults [55, 175, 176]. Very old people also typically exhibit a range of age-related changes to gait, including reduced hip motion [176], reduced ankle push-off power [241], reduced range of ankle motion [89, 176] and a larger degree of out-toeing [176]. These age-related changes in gait patterns are generally attributed to elderly people adopting a safer, less destabilizing gait in order to compensate for the destabilising effect caused by deteriorating sensory functions and muscle strength [241].

These changes are associated with normal ageing. However, there are certain changes in gait patterns that may be predictive of future falls. These are not limited to the elderly, but are more prevalent in this age group. For example, fallers walk significantly slower than non-fallers [152, 47, 145, 87].

There is some suggestion that step width may also have a predictive value, but the evidence is unclear. Murray *et al.* [175] found that step width increases significantly with normal ageing, but Gabell and Nayak [80] found no significant differences in mean step width between young and older adults. Guimaraes and Isaacs [87] reported that older people with a history of falling walked with a significantly narrower step width than age-matched controls, but their widely cited results are contradicted by similar investigations which reported no difference in step width [96] or an increased step width [82] in fallers compared with nonfallers.

Changes to gait may also be made in compensation due to a fear of falling. Maki [155] found that elderly subjects' fear of falling was associated with reduced stride length, reduced speed and increased double support time. The variability within parameters of gait appears to be a more sensitive predictor of falls and functional dependence than the absolute measure of the parameters. While mean differences in stride length, speed and double support times were not predictors of falls risk, stride-to-stride variability in these parameters were found to be independent risk factors for falling.

Hausdorff *et al.* [93] found that fallers walked with significantly greater variability in stride time, stance time and swing time but had walking speeds similar to the nonfallers. Lord *et al.* [145] found that those who fell more than once in one year had a more variable cadence than those who did not fall, or who fell only once.

Levels of variability are not consistent across parameters. Gabell and Nayak [80] reported that step width and double support time values were more variable than step length and step time in both young and old adults. They suggest that step length and step time are relatively stable parameters which determine the basic gait pattern while step width and double support time are the parameters most involved with dynamic balance control.

3.6.6 Accelerometry in Gait Analysis

Some of the earliest work on gait analysis using accelerometers (accelerograms) was carried out in 1964 by Liberson [137] who studied the major mechanisms of gait represented by movement of the hip, knee and foot in the sagittal plane. Accelerometers were attached to the left leg and the back, electrodes were attached to the left gastrocnemius muscle on the left leg, and a strain gauge tensiometer was attached to the left gastrocnemius muscle. He found correlations between the vertical and horizontal acceleration curves at the centre of gravity and parameters in the gait cycle. Some of these results are summarized in figure 3.11, which shows the relationships between the vertical and horizontal accelerations at the centre of gravity and other locations on the body, and muscle action during the gait cycle.

Twenty-seven years later, Evans *et al.* [70] demonstrated that components of the gait cycle could be identified from the three signals obtained from a single sacrum-mounted triaxial accelerometer. They used switches attached to the heel and forefoot of each foot to relate the signal from the triaxial accelerometer with the heelstrike and toe-off for each foot during a walk along a 20 m path.

Figure 3.12 shows accelerations recorded from a young person with normal gait. Inflections in the vertical channel signal can be used to identify the beginning of the step (heel-strike) and the end of the previous step (push-off). This means that temporal gait parameters, such as gait cycle time, right and left step times, double-support and single-support times can be measured from the accelerometer signal [56, 70]. Any asymmetry in the step times is also apparent and may be quantified. If the distance walked is known, then spatial parameters of mean walking speed and mean stride length can be calculated. The gait cadence can also be computed, and if the length of the walk is known, the walking speed can be calculated.

Differential GPS has been used to augment the data from a triaxial accelerometer

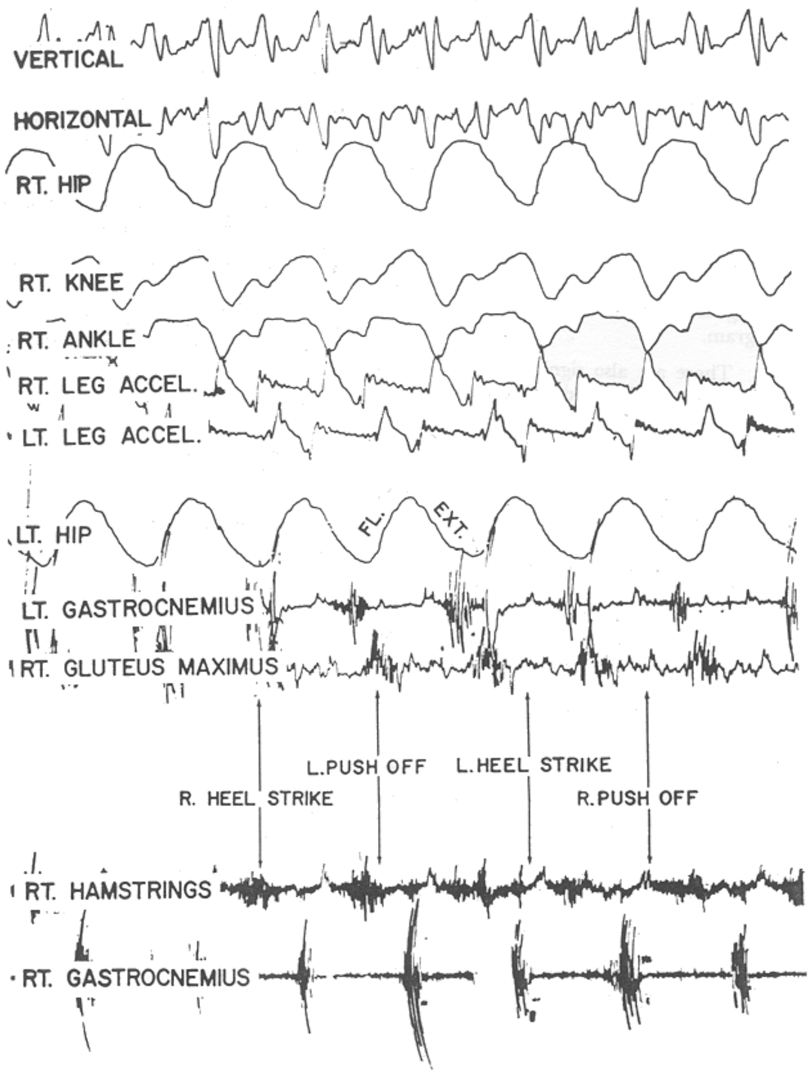


Figure 3.11: Series of tracings from a normal subject during walking, listed from top down: vertical and horizontal accelerograms; goniograms from right hip, knee and ankle; angular accelerograms from right and left legs; left hip goniogram; and electromyograms from left gastrocnemius, right gluteus maximus, right hamstrings, and right gastrocnemius muscles. Reproduced from Liberson [137].

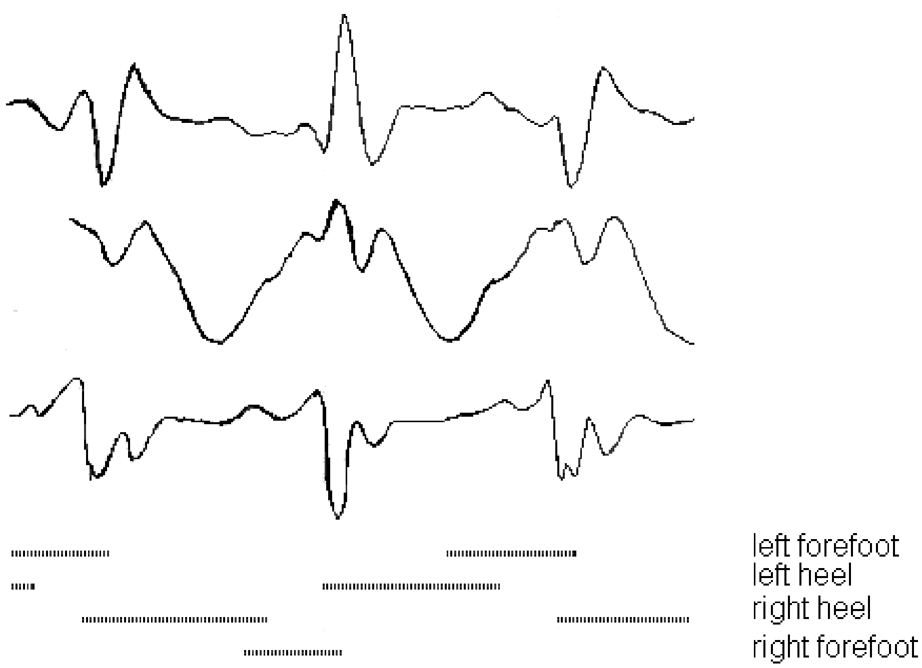


Figure 3.12: Three orthogonal acceleration signals from a normal healthy subject walking at a normal speed. Channel 1 (top) shows the lateral acceleration, channel 2 the up-down and channel 3 the anteroposterior signal. The fourth channel (lowest) is a signal from microswitches to show when the subject's heels and forefeet are in contact with the ground. Reproduced from Evans *et al.* [70].

so that the walking route and distance can be measured. Terrier *et al.* [211] attached the two instruments at the low back in eight subjects while they walked 150 paces along an athletics track at various speeds. The maximal and minimal speed and highest and lowest positions of the GPS during each gait cycle were identified. Heelstrike was determined as the lowest acceleration value for each step. There was an almost perfect correlation ($r = 0.9998$) between the step duration measured by the TA and that measured by the GPS.

Murakami *et al.* [173] conducted a similar experiment, except that they used two accelerometers to measure antero-posterior and vertical movement at the abdomen of a subject. The subject was free to walk around out of doors for a twenty minute period. They identified when the subject was moving and resting from the accelerometer signals, and compared these results to those obtained from the differential GPS. They found good agreement between the two sets of results.

Assessment of incline, speed and distance during unconstrained walking may also be possible using only accelerometers. Parameters such as the root mean square (r.m.s.) of vertical body accelerations, step length, and stride time are correlated to walking speed, although they are also dependent on the subject characteristics and the incline of the ground. Aminian *et al.* [20] conducted a study of incline, speed and distance assessment during unconstrained walking with 6 subjects. A triaxial accelerometer was attached to the back, and a uniaxial accelerometer was attached to the top of the right heel to measure heel forward acceleration. Subjects walked on a treadmill at various speeds and various inclines for a period of 15 minutes. The heel acceleration was used to identify the gait cycle. The mean, median and covariance of the four accelerations, the peak acceleration of the heelstrike, and the gait cycle duration were determined for each cycle. These 20 parameters were used as training inputs for two neural networks, one that estimated speed, and one that estimated incline of walking. Each subject then walked at a comfortable pace along an outdoor test circuit involving roads of various inclines. These walking patterns were presented to the neural networks, and speed (in $\mathrm{km.\,h^{-1}}$) and incline (in %) along the path were estimated. The standard deviation of the estimated incline was less than 2.6% and the maximum of the coefficient of variation between speed estimation was 6%.

Automated extraction of temporal gait patterns has been obtained using an additional accelerometer attached to the thigh. In another study, Aminian *et al.* [18] used two uniaxial accelerometers attached to each thigh to successfully determine the times of left and right heelstrikes and toe-offs during gait by means of an automated detection algorithm. Foerster and Fahrenberg [76] attached three orthogonal accelerometers to the sternum and a uniaxial accelerometer to each thigh. They then used a short-time Fourier transform on the vertical axis of the sternum accelerometer to determine the step rate. Bussmann *et al.* [38] studied the signals produced by a tangential uniaxial accelerometer attached to the thigh during walking. Six subjects walked with three different speeds. Simultaneous measurements were made with footswitches and an optoelectronic system. A clear relationship was found between the measured acceleration signals, and accelerations calculated from the optoelectronic system data. As a piezoresistive accelerometer was used, the gravitational acceleration influenced the amplitudes of the measured acceleration signal, but the shape and peaks of the signal were mainly determined by the body movement acceleration. They concluded that, despite the distortion of the body movement component acceleration by the gravitational acceleration component, this approach to gait analysis remained feasible.

The vertical acceleration component of the trunk- or back-mounted TA is the most important in the assessment of gait [31, 72, 76]. This is the component that is most sensitive to the presence of gait disorders [137], and from which elements of the gait cycle can most easily be identified [70]. The peak accelerations occur in this direction and reflect the magnitude of force applied at the approximate location of the centre of mass [199].

Smidt [199] defined a measure of smoothness of walking, called the harmonic ratio as the sum of the coefficients for the even numbered harmonics of the Fourier series, divided by the sum of the coefficients for the odd-numbered harmonics. The greater the harmonic ratio, the smoother the walking. They found it to be an effective method for discriminating between normal gait patterns gait patterns of subjects with gait defects. Farris [73] similarly found that symmetry in gait can be seen in the prominence of even harmonics in the accelerographic signal.

Preliminary research suggests that the power spectrum of the accelerometer signal can also be used to assess the stability of gait. In an initial study, a performance parameter based on the balancing forces as reflected in the power spectrum was successfully used to order different gait patterns in terms of relative stability [227].

3.7 Measurement of Physical Activity

The standard reference for the measurement of physical activity is the metabolic energy expended due to that physical activity [31, 195]. Metabolic energy expenditure can be measured relatively easily in a laboratory, but is difficult to measure directly in free-living humans. In a laboratory setting, direct calorimetry can be used. Direct calorimetry measures human heat production to determine energy expenditure. A subject is placed in a thermally insulated room that has a heat exchanger with circulating cold water. Energy expenditure is calculated from the rise in circulating water temperature. This method is very accurate but is clearly inappropriate for use on free-living subjects.

A wide range of techniques for the indirect measurement of physical activity have been developed, including direct observation, questionnaires and diaries, measurement of heart rate, oxygen uptake, determination of carbon dioxide production by the use of doubly labelled water, motion sensors and accelerometers [31]. Each technique has advantages and disadvantages. Direct observation, questionnaires and diaries are technologically simple, but are time-consuming and subjective methods. Radioisotope methods (using doubly labelled water) are costly and technologically complex. Heart rate monitoring is imprecise in many situations as heart rate responds to strains other than physical activity, including stress, posture, emotional status, circadian cycle, medications, and the effects of chronic disease such as chronic obstructive pulmonary disease (COPD) [201, 210].

Accelerometry provides an indirect method for assessment of physical activity that is portable, cost-effective and simple to use, and is not time-consuming for the subject [31, 201, 210, 74].

Indirect measurement of energy expenditure using accelerometry measures activity produced by muscular contractions. However, muscular contractions are only one of a range of energy uses in the body. Figure 3.13 shows a block diagram of the human energy system. The inputs of food and oxygen are converted to a range of outputs, including body waste, basal metabolism, fat, heat and muscular contractions. Thus, accelerometry provides a measure of energy that is utilised in activity, rather than a measure of energy input to the body.

Single-axis accelerometers (such as the Caltrac made by Hemokinetics in Madison, WI, USA) have been widely used to study physical activity and energy expenditure in healthy young and elderly populations [168, 181]. Multiple-axis accelerometers have been used to study energy expenditure in normal, active people [33], and in sedentary populations such as nursing home patients [126], patients with multiple

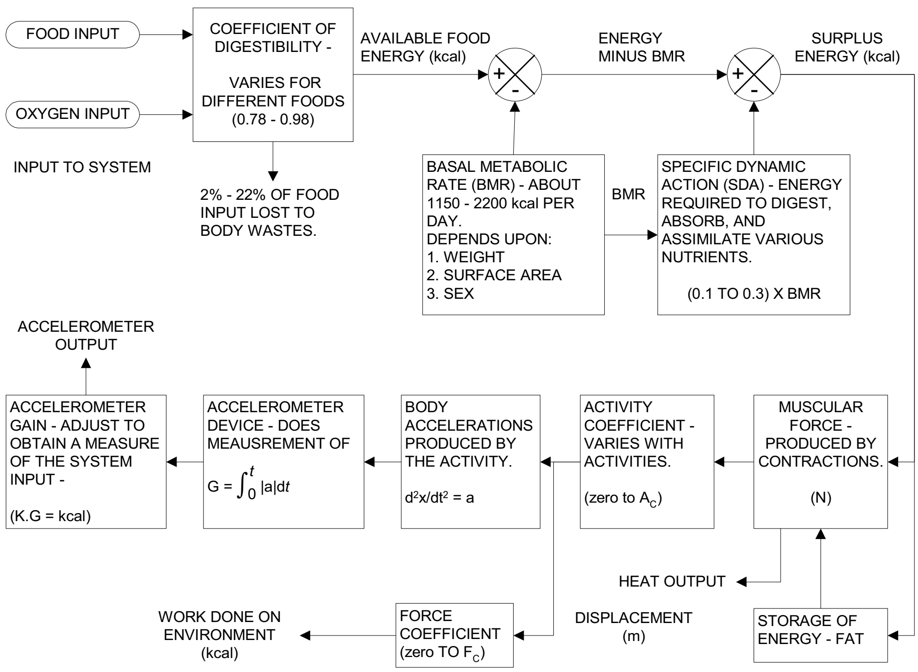


Figure 3.13: Block diagram of the human energy system. Adapted from Servais and Webster [195].

sclerosis [178], patients with COPD [201], and obese children [50, 68].

Many researchers who have investigated the validity of accelerometers as a tool for energy expenditure estimation in the activities of daily living report favourably on the device. Ng and Kent-Braun [178] studied a group of patients with multiple sclerosis, and groups of sedentary and active control subjects. They found that the triaxial accelerometer provided a more sensitive measurement of daily activity than self-report as measured by the 7-day Activity Recall Questionnaire. Bussmann *et al.* [39] compared energy expenditure estimates from heart rate to estimates from an accelerometer and found that accelerometry allowed more accurate measurement than heart rate, without the need for individual calibration. Steele *et al.* [201] presented preliminary data suggesting that a TA is a reliable, valid and stable instrument for measuring daily physical activity in COPD patients.

The metabolic energy expenditure (EE) estimate from an accelerometer is very accurate during walking on a level surface [34, 31, 210]. Interestingly, although the vertical acceleration component contains the most clinically useful information about gait [137], it is the antero-posterior acceleration that provides the best estimate of EE [34]. In a study in which 11 healthy male subjects walked on a treadmill at five different speeds, Bouten *et al.* [34] obtained a mean overall correlation between estimated and measured EE of 0.96. EE was estimated from the antero-posterior gait signal.

On the other hand, Fehling *et al.* [74] compared accelerometers with oxygen consumption, measured by indirect calorimetry, in older adults during exercise. The subjects wore the devices while walking on a treadmill and bench stepping at various rates. They found that the magnitude of the differences between the measured and estimated EE was dependent on exercise mode and intensity, which suggests that accelerometers are not suitable for monitoring of all physical activity. This is supported by other studies [98]. The body-fixed accelerometer attached at the waist mainly measures movement of the centre of mass. Activity that is concentrated in the upper body, such as weight lifting, or washing the dishes is significantly underestimated by a waist-mounted accelerometer [34, 98]. Nor are accelerometers able to measure the energy cost of walking up or down a slope, compared to walking on level ground [210].

In a controlled environment, a waist-mounted accelerometer provides an excellent estimate of energy expenditure in daily physical activity. Bouten *et al.* [31] compared the EE estimate from a TA to EE measured by indirect calorimetry. Thirteen young male subjects were tested. Each subject was placed in a respiration chamber of $14\,\mathrm{m}^3$ for a 36 hour period. The chamber contained a bed, table, chair, toilet, washing-bowl, radio and television. During the day time, subjects performed standardized daily activities that resembled normal daily activities. They achieved individual correlations between EE estimations and measurements between 0.87 and 0.97, with a pooled correlation coefficient of 0.89 across all subjects and activities.

Studies in which the EE was estimated by accelerometry for free-living subjects have achieved substantially lower correlation coefficients when the estimated EE was compared to the measured EE. Hendelman *et al.* [98] conducted a study in which 25 subjects completed four bouts of overground walking at a range of self-selected speeds, played two holes of golf, and performed indoor (window washing, dusting, vacuuming) and outdoor (lawn mowing, planting shrubs) household tasks. For all activities combined, the correlation between the estimated and measured EE was found to be only $0.59 - 0.62$ and was dependent on the type of activity performed. They attributed this to the inability of accelerometers to detect increased energy cost from upper body movement, load carriage, or changes in surface or terrain.

The placement and orientation of the TA device on the body have a negligible effect on the correlation between the accelerometer estimated EE and the measured EE. Bouten *et al.* [32] measured accelerometer output in the antero-posterior and vertical directions at the low back, and from this simulated accelerations at the shin, upper leg, trunk, lower arm and upper arm. The accelerations were compared to the metabolic energy expenditure. They concluded that they were able to use the accelerometer output at all examined locations to predict the EE with a high degree of accuracy.

A single TA seems to be the best instrument for prediction of EE. Although most movement is in the vertical direction, the addition of the remaining two dimensions significantly improves the accuracy of the estimate [31, 46]. Adding additional instruments at different locations on the body, for example, at the wrist, provides only a very slight improvement in accuracy, and does not justify the extra cost, complexity or inconvenience caused by the addition of a second instrument [32, 205].

Systems that use accelerometers to estimate EE use a model in which the integral of the modulus of the measured acceleration is linearly related to the energy expenditure due to physical activity. This relationship has been demonstrated for uniaxial accelerometers [170], and for triaxial accelerometers [31, 32, 201].

Bouten *et al.* [34] made a back-to-back comparison of different estimators of EE. Eleven healthy male subjects were assessed sitting, sitting with arm work, sitting and standing alternately (10 s each) and walking. EE was measured using indirect calorimetry, and a TA was worn at the sacrum. The following estimators were tested:

- $IAA_x = \int (|x(t)|)\, dt$, where x is the acceleration signal along the antero-posterior axis;
- $IAA_y = \int (|y(t)|) dt$, where y is the acceleration signal along the medio-lateral axis;
- $IAA_z = \int (|z(t)|) dt$, where z is the acceleration signal along the vertical axis;
- $IAA_{tot} = IAA_x + IAA_y + IAA_z$;
- $(IAA_x)^2$;
- $(IAA_y)^2$;
- $(IAA_z)^2$;
- $(IAA_{tot})^2$;
- $IAV = \int \left(\sqrt{x(t)^2 + y(t)^2 + z(t)^2} \right) dt$;
- $(IAV)^2$;

- $KE_x = \frac{1}{2} m_b \int x(t)dt$ = kinetic energy along the antero-posterior axis, where m_b is the subject's body mass;
- $KE_y = \frac{1}{2} m_b \int y(t)dt$ = kinetic energy along the medio-lateral axis;
- $KE_z = \frac{1}{2} m_b \int z(t)dt$ = kinetic energy along the vertical axis;
- $KE_{tot} = KE_x + KE_y + KE_z$ = total kinetic energy; and
- $P = \frac{d(KE_{tot})}{dt}$ = instantaneous power due to the rate of change of total kinetic energy at the point of attachment of the TA.

The best estimators were IAA_x and IAA_{tot}, both of which were linearly correlated to EE. The best estimator for walking was IAA_x (average individual correlation, $r = 0.99$), and the best overall estimator was IAA_{tot} (average individual correlation, $r = 0.91$).

The optimal regression equations were given by

$$\hat{E} = -0.176 + 0.085 \times IAA_x \text{ (best estimator for walking)} \tag{3.12}$$
$$\hat{E} = 0.104 + 0.023 \times IAA_{tot} \text{ (best overall estimator)} \tag{3.13}$$

Chen and Sun [46] tested 125 subjects in two 24 hour sessions. In the first session, the subject was asked to carry out a normal daily routine as closely as possible. In the second session, the subject engaged in a defined physical activity-exercise protocol. EE was measured using calorimetry and a TA was worn on the right hip. Two estimators were tested, one linear, and one nonlinear.

The linear model was

$$\hat{E}(k) = a_N \times H(k) + b_N \times V(k) \tag{3.14}$$

where $V(k)$ is the vertical acceleration (z-axis acceleration) at the k^{th} minute, $H(k)$ is the horizontal acceleration (equal to the square root of the sum of squared signals of the x- and y-axes) at the k^{th} minute, a_N and b_N are the regression parameters and $\hat{E}(k)$ represents the energy expenditure at the k^{th} minute.

The nonlinear model was

$$\hat{E}(k) = a_N \times H(k)^{p_1} + b_N \times V(k)^{p_2} \tag{3.15}$$

where p_1 and p_2 are regression parameters.

They found both model estimates were strongly correlated with EE. The differences between the measured and the estimated total EE were significantly decreased in the nonlinear model over the linear model ($p = 0.01$). Multiple regression analysis found that body mass was a significant factor ($p < 0.05$) in the determination of all regression parameters in both models.

In conclusion, accelerometry appears to provide a valid means of estimating EE in free-living subjects. The regression parameters and the accuracy of the approximation depend on the activity that is being undertaken. Bouten *et al.* found that the sum of the area encompassed by the magnitude of each of the three accelerations provided a good overall predictor of EE during daily activities. This is the estimator that was selected for use in the current work, where it was normalised with respect to time and is referred to as the (Normalised) Signal Magnitude Area.

3.8 Classification of Activities

Accelerometry systems have been used to identify and classify sets of postures and activities. Most of these systems have used multiple sensors; some systems have used only accelerometers, while other systems have used accelerometers together with another type of sensor. The most common placement locations are the chest or waist and the thigh [19, 37, 72, 76, 193, 207, 221, 225].

Algorithms for the detection of posture and motion patterns remain a crucial aspect of accelerometry, and the ability to achieve an adequate data reduction while still being able to differentiate between a variety of dynamic activities is still under investigation [76].

Pattern recognition strategies that use statistical algorithms, conventional or fuzzy logic, or artificial neural networks have been proposed [123], but only two approaches have been used to any extent. The first approach uses fixed-threshold classification while the second uses reference-pattern-based classification. In fixed-threshold classification, activities and postural orientations are discriminated by applying a threshold to the accelerometer signal. Thresholds are derived empirically. In reference-pattern-based classification, activity patterns are compared to template reference patterns. The studies outlined below use a combination of these two approaches.

A system developed by Veltink *et al.* [225] was used to distinguish between a set of static and dynamic activities, being sitting on a chair, lying on a bench (supine, prone, on right and left side), standing, walking (at slow, comfortable and fast speeds), ascending stairs, descending stairs, and cycling (at slow, comfortable and

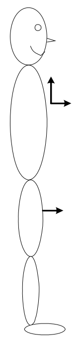


Figure 3.14: Illustration of the accelerometer mounting used by Veltink *et al.* Uniaxial accelerometers were mounted tangentially and radially on the sternum and tangentially on the thigh. The sensitive axes were all directed in the sagittal plane. Adapted from Veltink *et al.* [225].

fast speeds). One set of five normal male subjects (aged 23–42 years) was used to evaluate discrimination between static activities. A second set of five male subjects was used to evaluate distinction between static and dynamic activities and discrimination between dynamic activities. Subjects wore two uniaxial accelerometers at the sternum and one on the thigh (figure 3.14).

The signal from the tangential thigh accelerometer was used to distinguish between the static and dynamic activities, because leg movements were pronounced in all of the investigated dynamic activities. The algorithm used is shown in figure 3.15. This algorithm was based on the premise that the static or dynamic nature of activities can be determined by testing whether or not the signal varies with time. The signal was high pass filtered at 0.5 Hz to remove the d.c. offset. It was then rectified and low pass filtered at a cut-off frequency of 0.1 Hz to yield a measure for the averaged signal deviation from the mean. This was weighted with an exponential time window to provide a measure of "recent movement". The time constant of the exponential window was not described. The value of the resulting signal was compared to a threshold to decide whether the activity was static or dynamic. Dynamic activities were those in which the signal exceeded the threshold.

When an activity was identified as static, the mean values of the accelerometer signals over the period of activity were determined. The authors state that for distinguishing between sitting, standing and each lying position, the three accelerometers that were used were both sufficient and necessary.

Dynamic activities were distinguished by comparing the means and standard deviations of the mean signal values. Statistical differences were found between the results for each of the different activities tested, thus allowing discrimination

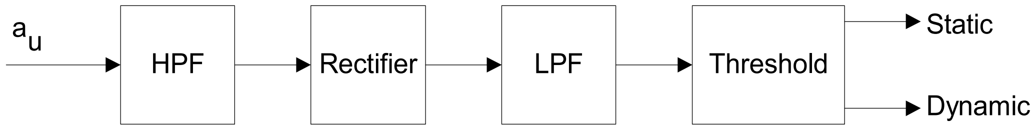


Figure 3.15: Detector of the static or dynamic nature of activities used by Veltink *et al.* The signal a_u of an uniaxial accelerometer mounted on the body is high-pass filtered, rectified and low-pass filtered. A static activity is detected if the filtered signal is lower than a set threshold, otherwise an activity is deemed dynamic. Adapted from Veltink *et al.* [225].

between the dynamic activities.

The choice of dynamic activities, and hence the algorithmic approach, was based on the assumption that "dynamic activities are normally achieved by cyclical movements". This is a very limiting assumption as it excludes dynamic activities of a short duration that are non-repetitive, such a sit-to-stand transitions which are an integral part of daily activity and which have known clinical significance.

A similar approach was used by Bussman *et al.* [37] who used a four accelerometers, one attached to each thigh, and two attached to the sternum. They low pass filtered each signal (0.5 Hz), and the results were used to distinguish between standing, sitting and lying. The remnant high pass filtered signals were used to distinguish between periods of movement and stationary activity based on the variability in the signal and the magnitude of the signal. Classifications were made every second. In a study of eight subjects, overall agreement between actual activity and the accelerometer classification was 90%.

Aminian *et al.* [19] further developed this approach. Five subjects each spent 1 hour in a studio-like room while wearing uniaxial accelerometers strapped to the chest and thigh. Activities were classified as lying, standing, sitting, walking or other movement. Here, too, a fixed threshold was used to distinguish between dynamic activities and resting states.

The algorithm is illustrated in 3.16. Each acceleration signal was low pass filtered at a cut off frequency of 0.5 Hz. The mean absolute deviation and the median were computed for every 1 s of signal. The resulting parameters were averaged over a 10 s period and compared to a pre-set threshold. Compared with video observation, the algorithm gave a 10.7% misclassification. This was mostly due to incorrect classification of standing when it was accompanied by a transition from another state, leading to the standing being classified as a dynamic rather than a static event. The misclassification between postural orientations was negligible.

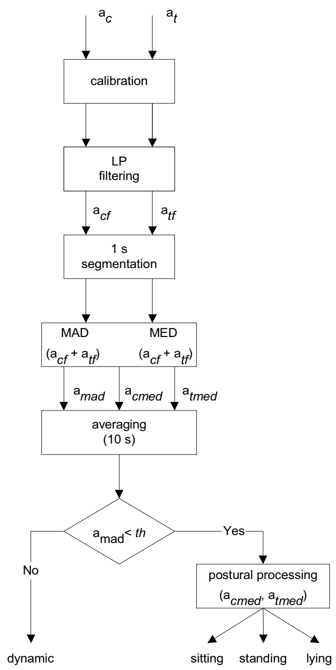


Figure 3.16: Algorithm for physical activity detection used by Aminian *et al.* Chest and thigh acceleration signals (a_c and a_t, respectively) were low pass filtered at a cut off frequency of 0.5 Hz. The mean absolute deviation (MAD) and the median (MED) were computed for every 1 s of signal. The resulting parameters were averaged over a 10 s period and compared to a pre-set threshold, th. Reproduced from Aminian *et al.* [19].

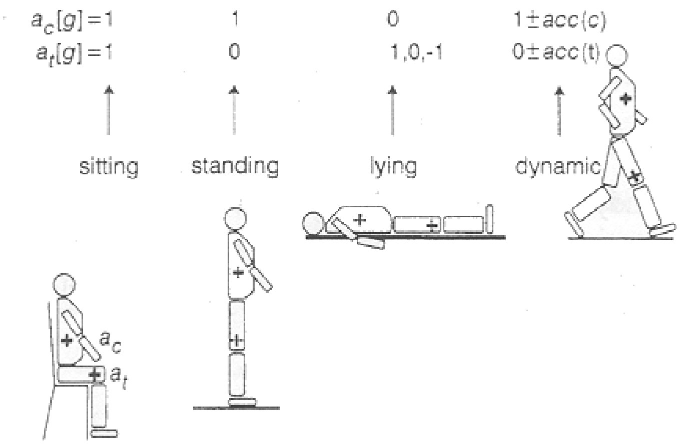


Figure 3.17: Relative values of chest a_c and thigh a_t accelerations during various movements. $acc(c)$ and $acc(t)$ represent chest and thigh acceleration variation during body movement. Reproduced from Aminian *et al.* [19].

Resting states were distinguished using the median signal values. The procedure that was used to discriminate between resting states is shown in figure 3.17.

Uiterwaal *et al.* [221] tested a similar system on a free-living subject for 6.7 hours. Two orthogonally mounted uniaxial accelerometers and a data logger were attached to the front of the waist. A third accelerometer was attached to the left thigh. Activities were classified as siting, standing, and locomotion. The overall (minimal) agreement obtained between video observation and the accelerometer system was 86.16%.

Fahrenberg *et al.* [72] employed multichannel accelerometry to discriminate between eight states in 26 healthy subjects: sitting, standing, lying supine, sitting while typing on a keyboard, walking, climbing stairs, walking downstairs and cycling. The placement of sensors is shown in figure 3.18.

The d.c. and a.c. components of the accelerometer signals were separated using a filter with cut-off frequency at 0.5 Hz. The d.c. components were averaged across each state. Similarly, the absolute values of the a.c. components were averaged across each state. The means and standard deviations of the d.c. and a.c. components of each accelerometer signal were calculated. A hierarchical classifier (figure 3.19) was developed based on five of these components. When the classifier was applied to a test data set, 97% of the activities were correctly classified.

In a second study, Foerster and Fahrenberg [76] extended this system to also distinguish between postural orientations during lying. The new system used a

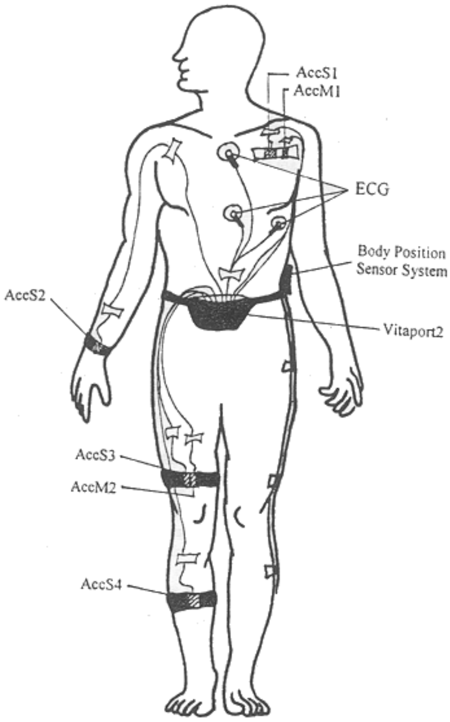


Figure 3.18: Placement of sensors and electrodes in the study by Fahrenberg *et al.* Reproduced from [72].

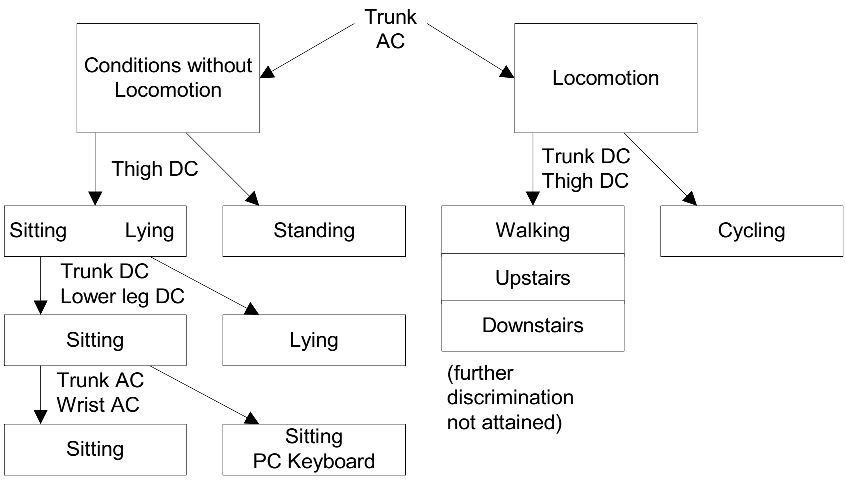


Figure 3.19: Classification of physical activity patterns using four accelerometer recordings. Adapted from Fahrenberg *et al.* [72].

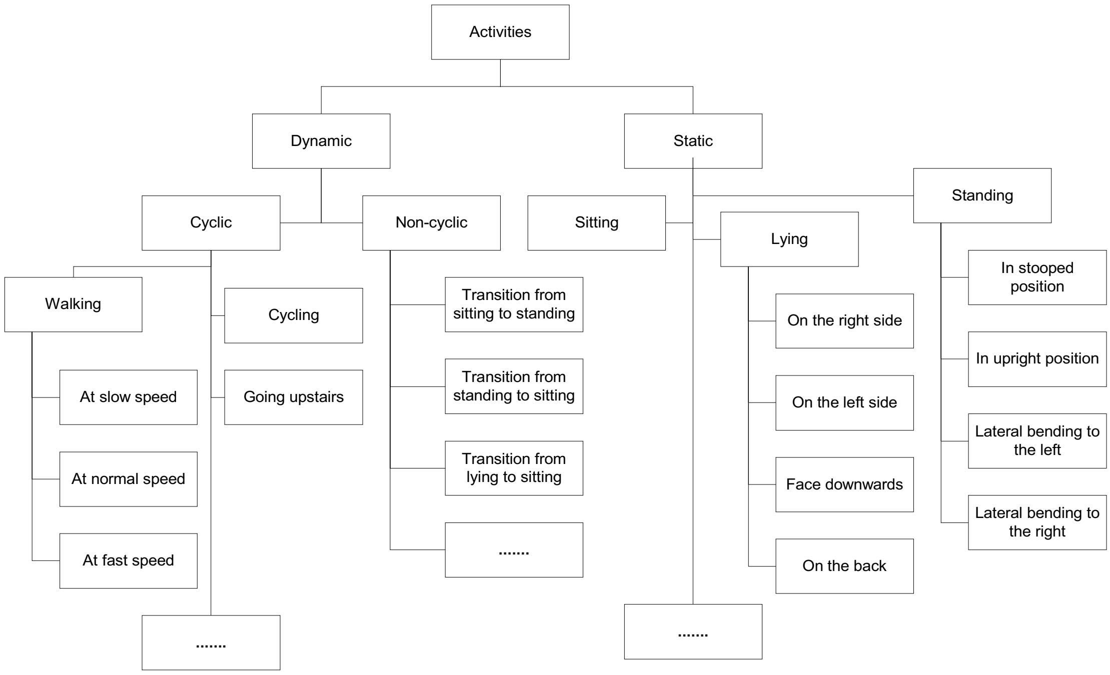


Figure 3.20: Classification tree for main relevant motor activities. Adapted from Kiani *et al.* [123].

sternum mounted triaxial accelerometer, and uniaxial accelerometers on each thigh. Again, a hierarchical classification strategy was used. The classification rate for this system was 96.8%.

A very different approach was taken by Tamura and Sekine *et al.* [193, 207] who used only a waist mounted triaxial accelerometer to perform activity classification. They distinguished between level walking, walking up a flight of stairs, and walking down a flight of stairs in 20 healthy male subjects. They used a Daubechies-3 wavelet analysis to derive an average acceleration vector for each activity. These averages were different for each activity and were used to discriminate between the three types of walking.

Each of these studies developed a specific algorithm to classify a specific set of activities. Kiani *et al.* [123] introduced a more general classification schema, which is shown in figure 3.20. A computerized analysis programme identified the onsets and endpoints of each different activity. The activities were then classified.

The physical system was similar to that of Bussman in that it consisted of an accelerometer attached to each thigh and a biaxial accelerometer attached to the chest. The accelerometers were wired to a waist worn data logger that could store data for 10 hours. Processing was carried out retrospectively.

They considered two approaches to classification: neural networks and signal processing techniques. In a preliminary study a neural network classified more than 95% of activity patterns recorded continuously over a ten hour period. However, the neural network was rejected because of the need to provide training sets tailored to every individual patient. Instead, signal processing techniques that could be used across all subjects were developed. Descriptive measures of the signals, including norm, mean, standard deviation, sine, cosine, Fourier transform, cumulative sum, inner and outer products, and maximum and minimum values were used to achieve the classification. This system achieved a 98% classification rate on 100 hours of data recorded from eleven male subjects.

Once classified, a set of relevant clinical parameters could be extracted from the data, including:

- total duration in lying posture;
- total duration in sitting posture;
- total duration in standing posture;
- total walking time;
- frequency of each activity;
- speed of walking; and
- transition times.

They remark that "this list of clinical parameters has been suggested by many clinicians".

3.9 Falls Detection

There is little published material available on automated fall detection using an accelerometer and no studies involving the use of accelerometers in falls monitoring and detection are known to the current author. There have been a small number of papers published that describe algorithms for automatically detecting falls by means of an accelerometer or ambulatory monitoring within a home telecare system.

A U.S. patent by Petelenz *et al.* [185] describes a system in which a one-dimensional accelerometer is used to detect fall events. The accelerometer is worn by the subject such that the sensitive axis is aligned to the vertical axis of the subject. The devices samples data and measures the angle, α, between the gravity vector and the sensitive axis of the accelerometer. This is a measure of whether or not the subject is upright. If α exceeds a threshold of 50° for at least 80% of samples over a certain number, N, of data points (i.e. the subject is no longer upright) then the system continues reading and storing angle data for at least another two seconds. After this, the system traces backward in the buffer to obtain the starting point of the movement. The fall discriminator then tests for falls by comparing the peak magnitude, the mean magnitude and the duration of the event to preset thresholds. If a fall is detected then the system sends a signal to a telephone dialer in order to generate a call for help. If no fall has occurred then the system waits until the subject is upright again and then returns to its original fall monitoring mode. The authors claim a rate of almost 95% fall detection using this system with data obtained from a waist mounted accelerometer although details of any studies that have been conducted are not disclosed.

A similar system was described in a U.S. patent by Lehrman *et al.* [134]. Their method measures the acceleration signal from a biaxial accelerometer worn such that both sensitive axes are horizontally aligned. The acceleration signals are filtered and monitored to detect (i) impacts and (ii) whether the subject is lying down. If these conditions indicate a fall then an alarm is generated. However, the authors make no comment on the performance of their system.

These systems were preceded by a design specification for a smart fall and activity monitor by Williams *et al.* [237]. Their design used a shock sensor to identify suitably large shocks. Shocks were identified by comparison to a preset threshold. If a sufficiently large impact was detected the device would monitor the orientation of the subject. If the subject was upright then the device would log the event but take no further action. If the subject had fallen then the device would wait 20 s before transmitting the alarm signal. If the subject managed to get up within this

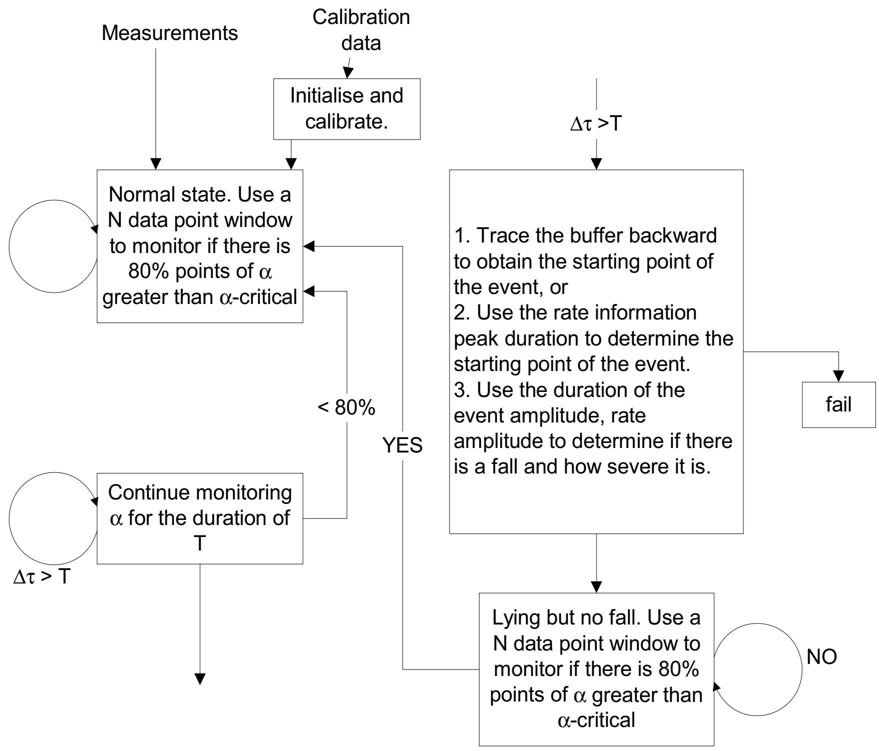


Figure 3.21: Method for detecting falls devised by Petelenz *et al.* Here, α is the angle between the subject and the gravitational vector, α-critical is a 50° threshold. T is a 2 s threshold, $\Delta\tau$ is the elapsed time. Adapted from U.S. Patent 6,433,690 [185].

time, the fall was logged and normal monitoring resumed, but if the subject failed to get up then the alarm was raised. Figure 3.22 illustrates the flow of processing logic for this system.

Doughty *et al.* [63] developed a system of the type described by Williams. They used a two stage detection process that used an impact sensor to detect an impact that exceeded a threshold value, followed by a second sensor that identified the postural orientation of the person. The sensors were contained within a single instrument. If a fall was detected the device was designed to use wireless communications to link to a community alarm system. The device was attached to a jointed mannequin at four different sites, being the chest, the waist, the wrist and the knee. The mannequin was subjected to fifteen falls and the algorithm was evaluated. They concluded that the device could, in practice, be placed at the chest or the waist and falls reliably identified.

3.10 Chapter Conclusion

Postural sway while standing, the sit-to-stand and the stand-to-sit transitions, and walking are complex movements that are affected by many factors including physique, age, and pathology. Even in the case of healthy people, these movements can be highly individualistic. Nonetheless, there are a set of basic parameters that are common to all instances of these movements and that have been shown to have clinical value in predicting changes in health leading to the onset of functional dependence or a fall event.

Accelerometers have been employed in studies to assess balance, gait, to classify activities, to identify falls and to estimate metabolic energy expenditure. In all cases, the results indicate that accelerometry is an approach that should be suitable for unsupervised monitoring of free-living subjects.

The next chapter describes the physical construction of an accelerometry system that was designed specifically for unsupervised, long term, home monitoring. This system uses only a single instrument, a triaxial accelerometer, that is designed to be attached to the waist of the subject.

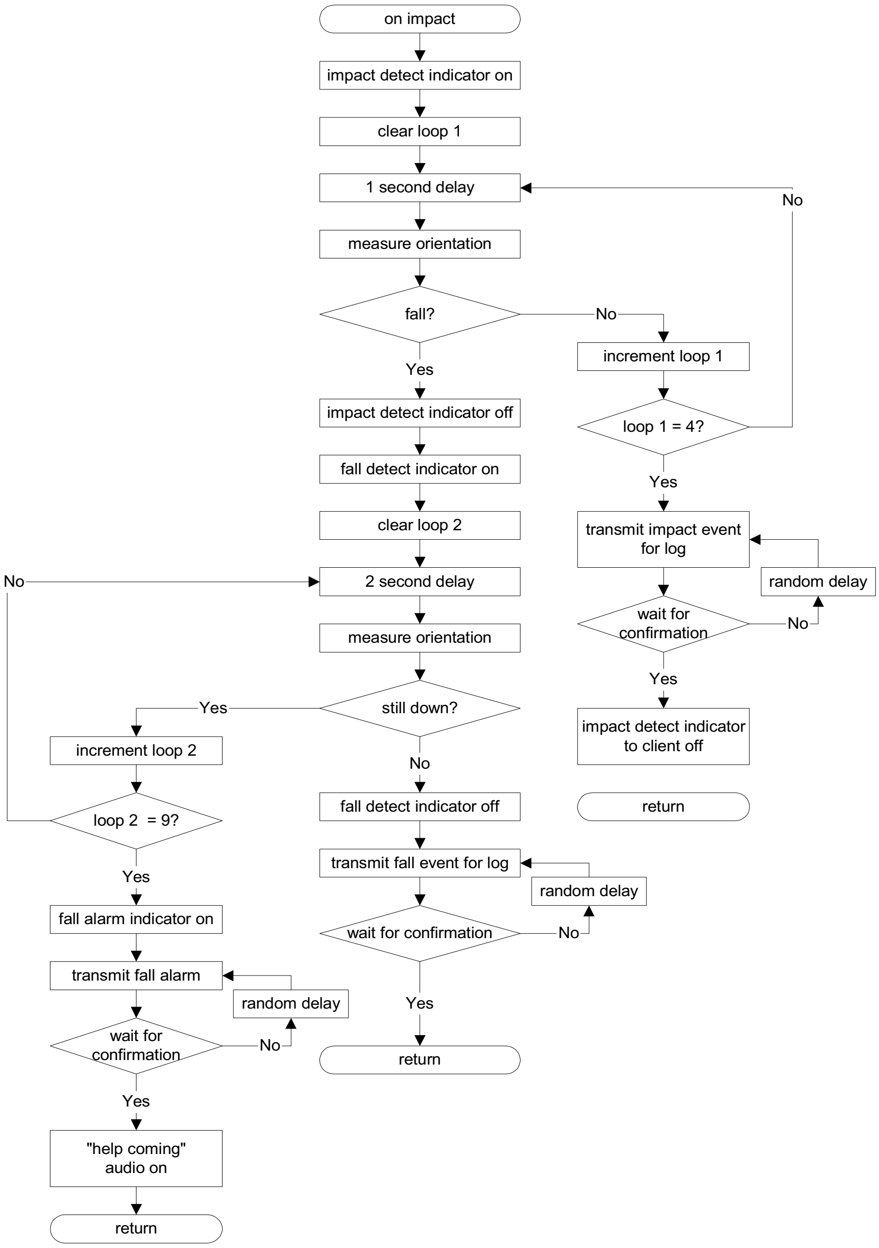


Figure 3.22: Fall monitoring device flow chart to establish nature of impact. Adapted from Williams *et al.* [237].

Chapter 4

The Home Monitoring System

4.1 Overview

This chapter describes the physical construction of an accelerometry unit that was designed for monitoring of human movement in an unsupervised environment over extended periods. The system consisted of a single triaxial accelerometer that was designed to be attached at the waist, a wireless transmitter unit, a receiver unit and a personal computer for data processing.

The first sections of the chapter are concerned with the design of the device. The latter sections of the chapter are concerned with the results of prototype calibration and testing for functionality and reliability.

4.2 Design Criteria

In choosing technology for unsupervised home monitoring both functionality and usability criteria need to be addressed. Functionality criteria specify what the technology must achieve. Usability criteria specify what is needed to ensure that the technology is able to be properly used.

In chapter 1 it was observed that any technology for unsupervised health monitoring must function reliably, ensure the security of personal data, be cost effective, minimise inconvenience to the patient, and must be acceptable to patients and health care workers. As patient compliance is essential to the functioning of the system, it must be designed to encourage use by being comfortable to wear and simple to use. It was decided to use an instrument that required a single point of attachment on the body.

As the instrument was to be worn, accessibility, size and weight were also issues of concern. The size and weight were equally important in that they affected the comfort of the subject. The device needed to be as light as possible, and small enough to be unobtrusive, but not so small that it was difficult to handle.

The instrument needed to be placed in a location on the body that was easily accessible to the subject, that did not cause comfort or inconvenience during routine daily activities, and from where useful body movement measurements could be obtained. In order to monitor whole body movements the device needed to be located as close as possible to the centre of mass (located within the pelvis). Here the measurements tend to be of "whole-body" activity, rather than of movements of the peripherals, such as thigh or hand movements. The majority of researchers using accelerometers for physical activity assessment have attached a device at waist level [31, 195]. Locating the device on a waist belt means that it is close to the centre of mass of the subject when standing. It was decided to design the TA device to attach at the waist, either on a belt, or to the waist of a skirt or a pair of trousers in a similar manner to that of a small pager unit. This approach was preferred to that of using a specialised belt or item of clothing as it allowed more flexibility in the use of the same device (the same unit was suitable for people of all shapes and sizes and did not limit choice of clothing.).

The sensor of choice was the accelerometer. (Obviously, other types of sensors could also be embedded into the instrument but the additional instrumentation increases both the cost and complexity of the system. As it is was not known what could actually be done with accelerometers in this environment, the current work focussed exclusively on determining how much information could be obtained from a three-dimensional accelerometer alone.) Accelerometers, in addition to being instruments that are becoming highly regarded in motion analysis, are also small, lightweight, and relatively inexpensive.

When used in a system for assessment of human movement, accelerometers must provide accurate measurement of the frequencies and acceleration amplitudes generated by the movement. An amplitude range of $\pm 6\ g$ and a frequency range of 0–20 Hz are required for assessment of human movement by an accelerometer located at the waist [31].

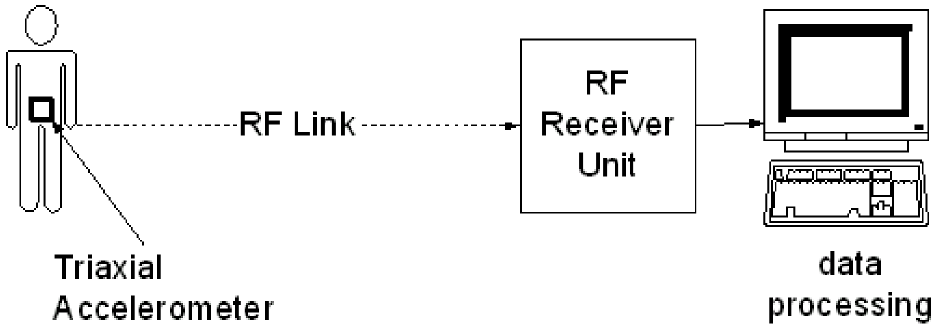


Figure 4.1: Block diagram of the home ambulatory monitoring system. The instrument containing the triaxial accelerometer is worn at the waist by the subject. Data are captured and transmitted via wireless link to a receiver unit from where they are transferred to a personal computer for processing.

4.3 System Design

4.3.1 Introduction

The accelerometry system that was used in the current work was designed by the Biomedical Systems Laboratory at the University of New South Wales, specifically for long term, unsupervised home monitoring of human movement. The current author was involved in the specification of the technology (required amplitude and frequency ranges, package size, etc.) and in the functionality testing, calibration and validation of the system, but was not involved in the physical design process, nor in the construction process of this system.

Figure 4.1 shows a block diagram of the ambulatory monitoring system. It consisted of an ambulatory monitor, a receiver unit and a personal computer.

4.3.2 The Ambulatory Monitor

The ambulatory monitor consisted of a single wearable unit. This was a small pager case (size: $71 \times 50 \times 18$ mm) that was designed to be clipped on to a waist belt. This size was deemed to be small enough to be unobtrusive when worn, but large enough to be easily handled. The instrument is shown in figure 4.2

There was no commercially available triaxial accelerometer that could meet the monitoring requirements of this project known to the design team. Consequently, a triaxial accelerometer was constructed from two biaxial accelerometers. The accelerometers that were chosen were ADXL210s, supplied by Analog Electronics. These devices had a range of $\pm 10\ g$, a frequency range of $0 - 500$ Hz, an r.m.s.

Figure 4.2: Photograph of the ambulatory monitor. The accelerometers were contained in a pager casing measuring $71 \times 50 \times 18\,\text{mm}$.

noise estimate of 4.33×10^{-3} g and a peak-to-peak noise estimate of 17.2×10^{-3} g (95% confidence interval). These devices respond to both acceleration due to movement, and gravitational acceleration, g (approximately $9.81\,\text{m.\,s}^{-2}$). As there were four uniaxial accelerometers measuring three dimensions, one of the dimensions was measured twice. The redundant signal was transmitted but not recorded or processed.

In addition to the triaxial accelerometer, the monitor contained a wireless transmitter, a push-button and a green light. The unit was designed to use very low rates of power, and was powered by one 1.5 V AA dry cell alkaline battery. The monitor, including the battery, weighed approximately 50 g.

Each of the accelerations was sampled at 125 Hz and output from the ADXL210 as the duty cycle component of a pulse wave. The duty cycle duration (X) and pulse wave period (T) were counted using 12-bit counters counting off a 1.288 MHz clock. The acceleration could be computed by dividing the duty period count by the pulse wave period count. This gave the value of the acceleration as a fraction of the total acceleration range of ± 10 g. For example, an acceleration of 0 g was represented by a value of 0, while an acceleration of $+5$ g was represented by a ratio of 0.75. In order to provide anti-aliasing, the outgoing signals were filtered by a low-pass RC filter with a cut-off frequency of 50 Hz. The first biaxial accelerometer was polled and its data stored in a buffer. The second biaxial accelerometer was then polled and its data stored in the same buffer. Two other bits of data were added to the buffer's contents. These bits indicated the status of the push-button (on/off) and the level of the battery (low/not low). The buffered data were then transmitted as a packet to the receiver unit before the next set of data was polled, buffered and transmitted. This approach was adopted due to memory limitations in the very low powered integrated circuits (ICs) that were available at the time of development. More sophisticated ICs that had more available memory required levels of power that were unacceptably high for the design.

The push-button firmware included a 1 s delay before responding with the button pressed signal. This was designed to prevent inadvertent knocking of the button being registered as a push-button press.

4.3.3 Data Transmission

Radio frequency (RF) communications were chosen for this application rather than higher frequency line-of-sight transmission. Although RF communications are more susceptible to interference and security breaches, they have the advantage of being able to pass through walls and "bend" around corners. In a home environment this means that a single RF receiver can be used rather than needing repeaters or receivers to be placed in each room.

The buffered data were transmitted at 19.2 kbps via a 433.92 MHz wireless link using bi-phase mark encoding. The data packets received by the RF receiver were checked for errors. If an error was detected, the packet was discarded but not re-sent. If the data packet was not in error, it was transmitted via a RS-232 connection to a personal computer. The data packets were time-stamped as they were received by the personal computer. All of the data processing and storage was carried out at the personal computer. The resultant data sampling rate was 45 Hz and the data resolution was better than $25 \times 10^{-3}g$. The down-sampling was caused by data being lost from one biaxial accelerometer while data from the other biaxial accelerometer was polled and buffered, and by data loss during transmission. This led to the possibility of some aliasing in the signals.

Both of these losses could be overcome by redesigning the TA unit using a very-low-power processor with more memory such as are now becoming available. This would allow the data to be buffered without loss, and would also allow for error correcting transmission and lost packets could be re-sent. Suggestions for modification of the hardware, based on the findings of the current work, are made in chapter 9.

However, it was found that the reduced data rate had a negligible aliasing effect. As essentially all of the measured body movements were contained below 20 Hz (indeed, even in gait, 99% of the energy is contained below 15 Hz [21]), only white noise was present in the signal between 20 and 50 Hz, and so this uniform, random noise was the only signal component to be reflected from the higher to the lower frequencies during the signal down-sampling.

4.3.4 The Receiver Unit

The receiver unit provided an interface between the transmitter unit and the personal computer. The receiver unit recoded the wireless transmission into RS-232 format and sent it to the personal computer for storage and processing.

4.3.5 The Personal Computer

There were strong arguments both for and against the use of a personal computer for the data processing and storage. If a subject does not own a computer, then the inclusion of such greatly increases both the expense and the bulk of the system over a system in which a customised data storage and processing module is built into the receiver unit. On the other hand, the personal computer provides a more flexible solution. The development times and costs are reduced as the hardware is already readily available. Maintenance is also much easier on a personal computer than on a dedicated system. Additionally, over half of households in Australia already own at least one personal computer [11], and this figure is expected to continue to increase. In these homes, using the existing infrastructure may be more convenient and cost effective than providing customised system hardware.

The system employed in the current work used a personal computer in order to take advantage of the flexibility that it provided. This allowed all of the data from the wearable instrument to be captured continuously and stored for processing. Additionally, during field trials with the system (discussed in chapter 7), the computer interface was used to provide instructions to the subjects.

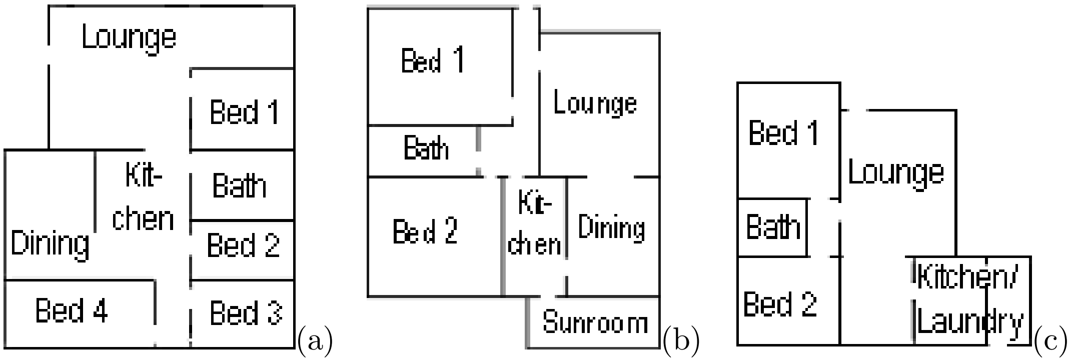


Figure 4.3: Sketches of the homes in which the TA system was tested. Not to scale. (a) 4-bedroom fibro home; (b) 2-bedroom brick home; and (c) 2-bedroom brick veneer home.

4.4 Reliability - Transmission Range and Power Consumption

The transmitter design focused on energy efficiency. Power consumption was a concern as it dictated the frequency at which the battery in the ambulatory monitor needed to be changed. The wearable unit consumed 15 mA from a 1.5 V source when transmitting 0 dBm into a 50 Ω surface mount planar antenna. At this level of power consumption, the device was able to transmit data continuously for 80 hours before the battery (an alkaline AA non-rechargeable battery) needed to be replaced.

The telemetry system functioned reliably over a range of 50 m line-of-sight. In the laboratory, where there was a lot of electronic noise and thick concrete walls separating rooms, the device functioned reliably within the room in which the receiver unit was placed, and within the neighbouring rooms, but not when there were two or more walls between the transmitter and the receiver.

The system was tested in three homes (figure 4.3). The receiver unit was placed in one room of the house, and an investigator moved around all of the rooms in the house with the TA unit and the continuity of the received signal was monitored. The first home was a 4-bedroom weatherboard house. The second and third houses were 2-bedroom brick homes. In each cases, the system functioned reliably throughout the house.

4.5 Calibration of the Ambulatory Monitor

4.5.1 Theory

When a piezoresistive accelerometer is placed with the sensitive axis parallel to the gravitational vector, the accelerometer should give a reading of +1 g. When it is placed with the sensitive axis antiparallel to the gravitational vector, it should give a reading of -1 g. When the sensitive axis is perpendicular to the gravitational vector, the accelerometer should give a reading of 0 g. This information was used to calibrate the d.c. response of the triaxial accelerometer. The device was aligned in 6 different orientations, each having one of the orthogonally-mounted uniaxial accelerometers either parallel or antiparallel to the gravitational vector. At each position, the responses of each of the three accelerometers were recorded.

The responses were adjusted using the linear equation $y = mx + b$ where x is the measured value, y is the actual value, and m (the gradient) and b (the y-axis offset) are calibration parameters. The parameters were set using the measured values corresponding to $y = +1$ and $y = -1$. The measured values corresponding to $y = 0$ were used to check the results.

4.5.2 Results

The offsets inherent in the ADXL210 devices were all within the manufacturer's tolerances of +/- 0.01° between the two axes. The main component of the d.c. offset of the accelerometer was due to the physical mounting inside the casing. The orientation of the accelerometers relative to the casing varied slightly between instruments.

The d.c. calibration parameters for one triaxial accelerometer were

	m	b
a_1	1.07	-0.10
a_2	1.08	0.34
a_3	1.06	0.11

These values were typical of the d.c. calibration values found across all seven instruments that were developed.

4.5.3 Calibration Drift

One unit was tested over a 2 year period for drift in calibration. Once the unit was constructed, there was some drift in the d.c. offset (a change of up to 0.2 g) over the first few weeks of use. This is attributed to some mechanical shifting of the components during this time. After this period, the calibration was tested every 6 months and was found to remain constant with negligible drift. Similar results were found in the six units that were used in a field study with elderly subjects (refer to chapter 8). The calibrations drifted slightly ($< 10\%$) in the first two to three weeks, but then remained steady for the rest of the study.

4.6 Chapter Conclusion

A wireless, wearable triaxial accelerometer unit was developed by the Biomedical Systems Laboratory at the University of New South Wales. This unit was designed to attach easily and comfortably at the waist. It was enclosed in a small pager casing, and weighed only 50 g including the 1.5 V AA battery used to power the instrument. The instrument was designed to function on very low power. Data from the instrument were continuously sampled and transmitted at an effective rate of 45 Hz over a 433.92 MHz wireless link to a receiver unit attached to a personal computer where they were processed and stored. The accelerometer characteristics of ± 10 g, and 0–22.5 Hz met the required ranges of ± 6 g and 0–20 Hz specified by the literature for assessment of human movement at the waist.

The system functioned reliably in the three homes in which it was tested. It had a line-of-sight transmission range of 50 m and a life of 80 hours of continuous transmission from a single 1.5 V alkaline battery. When the units were first constructed, there was some d.c. calibration drift due to physical readjustment of the components inside the casing, but once the unit was “worn in”, the calibration remained steady. Possible improvements to the design of the triaxial accelerometer unit are discussed in chapter 9.

Chapter 5

Understanding the TA Signal

5.1 Overview

Before the accelerometer system can be used in any monitoring context, and before algorithms can be developed to interpret the data recorded by the system, it is necessary to have an understanding of the nature of the signals produced by the triaxial accelerometer (TA) unit. The purpose of this chapter was to study the behaviour of a single waist mounted TA and to establish the capabilities and limitations of such a system in monitoring human movement.

In this chapter the signals obtained from a body-fixed piezoresistive TA are analysed. The signals are described in a theoretical and an experimental context. An understanding of the nature of the signals is developed, and the means by which they can be represented are discussed, together with the advantages and disadvantages of each representation. The measurement of movement using a TA is discussed. This chapter also addresses the questions of "How does the device placement affect the TA signal output?" and "How reliably can the TA signals be interpreted, given some noise in the signal, and some variation in the device placement?".

The chapter begins by developing a theoretical understanding of the signals from a TA, based on the physical properties of the instrument. The signal is made up of several components, and each of these is examined. Difficulties in distinguishing between the different signal components are discussed.

Section 5.3 investigates different ways of representing the signal from the TA device in order to make the best use of the information contained in the signal.

Section 5.4 investigates the effect of placement location on the TA signals. This work provides an insight into the nature of the signals from an experimental view-point. It also allows the questions pertaining to robustness and flexibility in positioning of the device to be addressed. The effect of device placement is investigated for various postural orientations during rest, for the sit-to-stand and the stand-to-sit transitions, and for walking.

TA devices have been used to provide an estimate of metabolic energy expenditure. The final part of the chapter investigates the effect of filtering to remove noise and the effect of device placement on the estimates of metabolic energy expenditure.

5.2 Composition of the TA Signal

5.2.1 Introduction

Triaxial accelerometers suitable for application to human movement are not readily available and are not widely used outside of their use as estimators of metabolic energy expenditure. In order to work with these devices in new applications of unsupervised monitoring it is necessary to first gain a thorough understanding of the nature of the signals obtained. This understanding is developed by studying the composition of the TA signals from first principles.

The signal measured by each fixed-body piezoresistive accelerometer is a linear sum of five components, measured along the sensitive axis. These components are

1. acceleration due to body movement;
2. acceleration due to gravity;
3. accelerations caused by external vibrations not produced by the body (for example, jolting felt while driving in a car);
4. artefact due to bouncing of the sensor on the body due to loose attachment or soft tissue movement, or knocking of the sensor against other objects (for example, knocking against a wall); and
5. noise intrinsic to the measurement system.

The first two components provide information about the wearer of the device. The last three components are noise. The third component can reasonably be neglected in a home environment (except, perhaps, in the event of an earthquake!). The fourth component can be minimised by proper design and placement of the sensor. The fifth component, noise intrinsic to the system, can be reduced by careful design and choice of components. Filtering techniques can also be used to improve the signal-to-noise ratio.

The noise intrinsic to the TA system was measured in the following study.

5.2.2 A Study of the Noise Intrinsic to the System

Introduction

The TA device design results in a theoretical specified r.m.s. noise estimate of $4.3 \times 10^{-3}\ g$, and a 95% probability peak-to-peak noise estimate of $17.2 \times 10^{-3}\ g$ (refer to section 4.3.2). In this study, the noise levels intrinsic to the TA device were measured experimentally.

Experimental Procedure

A TA unit was placed on a table located close to the receiver unit and left untouched for 24 hours. The accelerations measured along each of the three axes were recorded. The range of signal fluctuation was measured.

In order to observe the performance of the system when subject to electrical interference, the TA was then placed on a bench in an electrically noisy laboratory for 28 minutes. The laboratory contained 10 computers and monitors, and other electrical equipment including signal generators and oscilloscopes. The accelerations measured along each of the three axes were recorded.

Data Analysis

The data were analysed retrospectively in Matlab version 6. Descriptive statistical measures—mean, 90% trimmed mean, range, interquartile range, and standard deviation (equivalent to the noise r.m.s.) were calculated.

Results

Figure 5.1 shows a part of the signals that were obtained while the TA device was resting on the table. Most of the signal was contained within a small acceleration band, but there was one spurious, large peak of noise present on two of the axes. (This is visible in the figure near the 100-minute mark, on the x- and y-axes.)

The results obtained when the device was placed in the noisy laboratory environment for 28 minutes were very similar, but there were more spurious, larger peaks of noise occurring randomly across channels and across time. In this instance, there were approximately 7 large noise spikes occurring on each of the three axes. Given

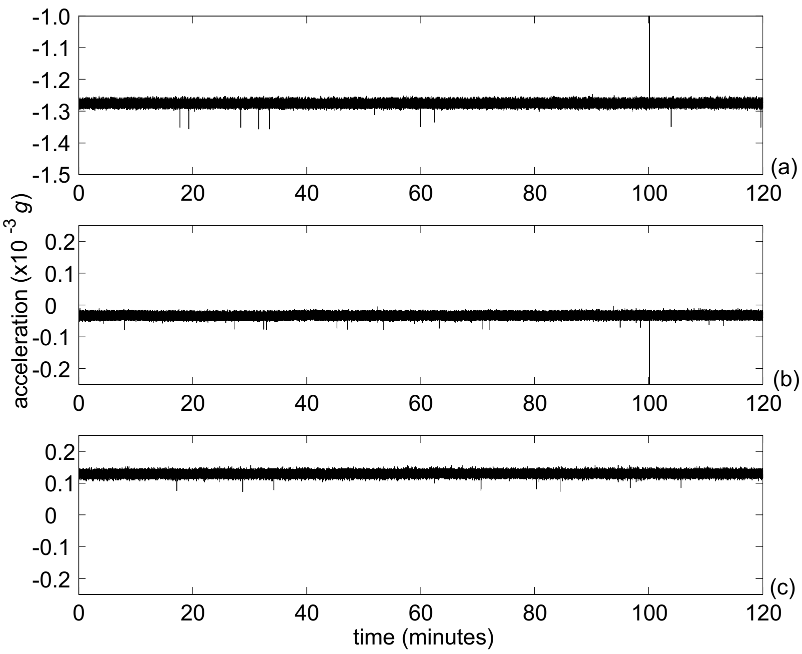


Figure 5.1: Signals obtained from the TA while it was resting on a table. The three acceleration components, (a) x-axis, (b) y-axis and (c) z-axis are shown.

that approximately 75600 samples were recorded from each axis, this represents a corruption of 0.0094% of the received data.

Descriptive statistics for the two tests are given in table 5.1.

When a median filter of length 3 samples was applied to the signal in order to filter out the large noise spikes the experimental results corresponded closely to the nominal r.m.s. noise estimate of 4.3×10^{-3} g and a peak noise estimate of 17.2×10^{-3} g. The descriptive statistics for the two tests, after median filtering are given in table 5.2. The technique of median filtering is discussed in section 5.2.3.

Discussion and Conclusion

The large, spurious noise spikes were due to interference and were added to the signal during transmission. They were not part of the signal measured by the TA. These spikes occur more frequently when the received signal is very weak, either because the TA unit is almost out of range of the receiver, or the TA battery is low. They also occur more frequently when the TA is placed in an environment with large amounts of electrical noise. This was confirmed by hardwiring the TA to the receiver unit and placing the system in the same electrically noisy environment. This time, in a 28 minute period, no large spikes appeared in the recorded signal.

	24 hour test			28 min, noisy conditions		
	x-axis ($10^{-3}g$)	y-axis ($10^{-3}g$)	z-axis ($10^{-3}g$)	x-axis ($10^{-3}g$)	y-axis ($10^{-3}g$)	z-axis ($10^{-3}g$)
mean	-1276	-37	129	-31	-44	993
median	-1276	-37	129	-31	-44	993
90% trimmed mean	-1275	-37	128	-31	-45	993
r.m.s. (mean removed)	5.9	5.8	5.9	6.6	6.1	6.5
peak-to-peak noise	1383	628	113	488	403	438
99% peak-to-peak noise	30	29	30	30	28	29
95% peak-to-peak noise	24	22	21	24	22	24
interquartile range	8	8	9	6.6	6.1	6.5

Table 5.1: Descriptive statistics for static noise levels in the TA. The different mean values between the two tests are due to the device being oriented differently in the two tests.

	24 hour test			28 min, noisy conditions		
	x-axis ($10^{-3}g$)	y-axis ($10^{-3}g$)	z-axis ($10^{-3}g$)	x-axis ($10^{-3}g$)	y-axis ($10^{-3}g$)	z-axis ($10^{-3}g$)
mean	-1276	-37	129	-31	-44	993
median	-1276	-37	129	-31	-44	993
90% trimmed mean	-1275	-37	129	-31	-44	993
r.m.s. (mean removed)	4.0	4.2	4.0	4.1	3.9	4.0
peak-to-peak noise	45	100	55	36	31	32
99% peak-to-peak noise	20	22	21	18	19	20
95% peak-to-peak noise	16	16	15	18	16	16
interquartile range	5	6	6	6	4	6

Table 5.2: Descriptive statistics for static noise levels in the TA device after median filtering ($n = 3$)

In this study, even with the additional noise interference in the second test, the 99% probability peak-to-peak noise was no more than 30×10^{-3} g, and the r.m.s. noise was only 6.6×10^{-3} g. After the signals were low-pass filtered using a median filter all of the large noise spikes were removed and the results were in close agreement with the nominal noise values. This indicates that low pass median filtering is an appropriate method for removing these noise spikes from the signal.

It can be concluded that the device operates within its design specifications, and with a r.m.s. noise level of at most 6.6×10^{-3} g, and a 95% peak-to-peak noise level of less than 30×10^{-3} g.

5.2.3 Median Filtering to Remove Noise

It is desirable to remove as much of the noise from the signal as possible prior to processing. The TA unit produced noise levels less than 30×10^{-3} g, or 0.15% of the accelerometer amplitude range. However, there was some susceptibility to noise during the wireless transmission. Observation of the received signals showed that occasional noise spikes were being added to the signal during the wireless transmission. Some of these spikes were occurring within the 5–20 Hz band; that is, within the frequency band containing the signal of interest. It was obviously desirable to remove these noise spikes, some of which had amplitudes greater than 10 g, i.e., greater than the range of the instrument! However, the noise spikes within the frequency band of interest could not be removed by a linear low pass filter without removing part of the signal as well, so a nonlinear low pass median filter was applied to the signal to remove noise spikes that occurred at frequencies below 20 Hz. This was carried out before any analysis of the signal took place.

Median filtering is a non-linear technique that applies a sliding window to a sequence. The centre value in the window is replaced by the median value of all the points within the window. For example, the ordered sequence, $\{4, 3, 5, 2, 8, 9, 1\}$, upon application of a median filter of length 3, becomes $\{4, 4, 3, 5, 8, 8, 1\}$. This allows a noise spike to be removed from a signal. For example, the ordered sequence $\{3, 3, 3, 7, 3, 3\}$, when filtered with a median filter of length 3, becomes $\{3, 3, 3, 3, 3, 3\}$. An example of the effect of median filtering on noisy data is shown in figure 5.2.

When applied to a signal containing body movement, the median filter has a dampening effect on the raw signal. Figure 5.3 shows the effect of applying median filters of lengths 3, 7 and 13 to the vertical component signal obtained when a subject is walking. Figure 5.4 shows the effect of applying the same filters to the

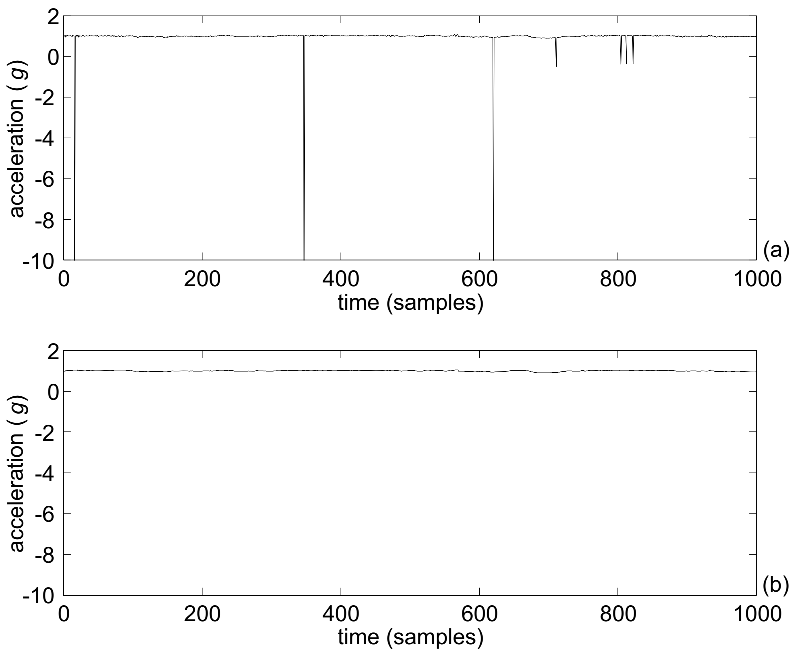


Figure 5.2: Effect of median filtering on a signal with noise spikes. (a) Raw signal, and (b) Signal after median filtering with a filter of length 3 samples.

vertical component signal obtained from a stand-sit-stand movement.

The quantitative effects of the median filtering on the signal are examined in later sections (section 5.5.2 and section 6.5).

5.2.4 Understanding the Gravitational Component

Piezoresistive accelerometers respond to gravitational acceleration. This is also referred to as the d.c. response, or the static component. These two names are slightly misleading, as the gravitational acceleration response does not have to be static. If the accelerometer is rotated, the gravitational response measured by the sensitive axis will change. Thus, in the current work, this component is referred to as the gravitational acceleration, or GA component. The GA component reflects the orientation of the device. If an accelerometer is placed, unmoving, in a gravitational field, it will result in an output reading of

$$acceleration = \tilde{g}\cos(\phi), \tag{5.1}$$

where $\tilde{g}$ is the gravitational acceleration vector and ϕ is angle between $\tilde{g}$ and the direction of the sensitive axis. This is illustrated in figure 5.5.

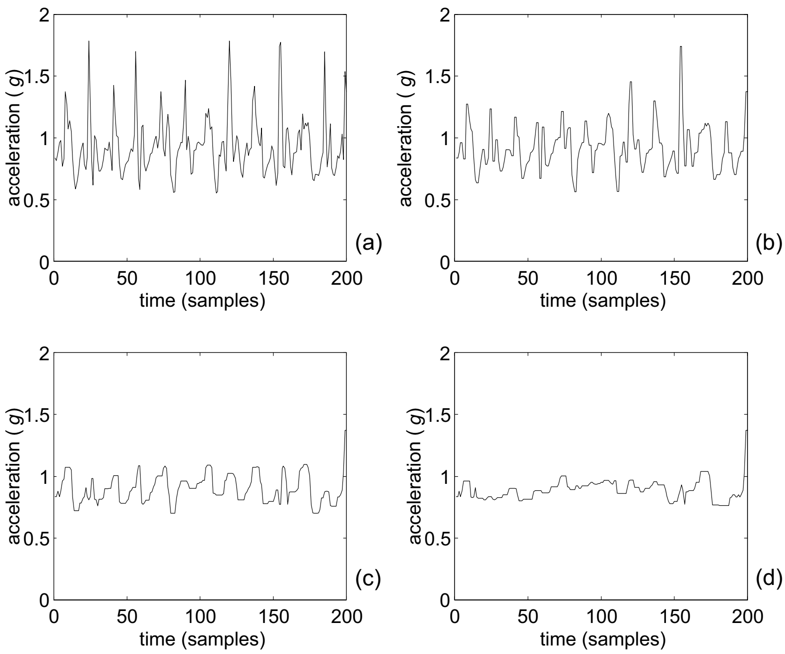


Figure 5.3: Effect of median filtering on the vertical component of a walking signal. (a) raw signal, (b) median filter length $n = 3$, (c) $n = 7$, (d) $n = 13$.

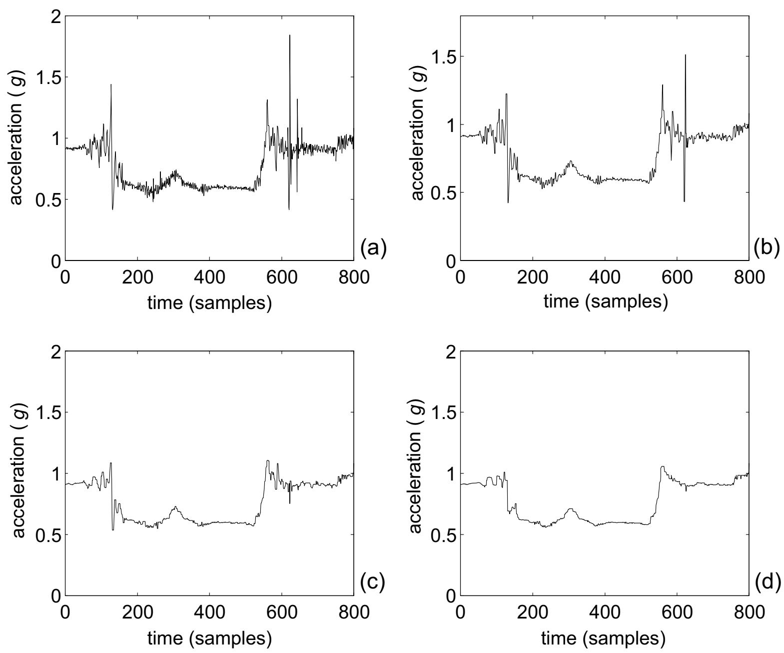


Figure 5.4: Effect of median filtering on the vertical component of a stand-sit-stand movement. (a) raw signal, (b) median filtering length $n = 3$, (c) $n = 7$, (d) $n = 13$.

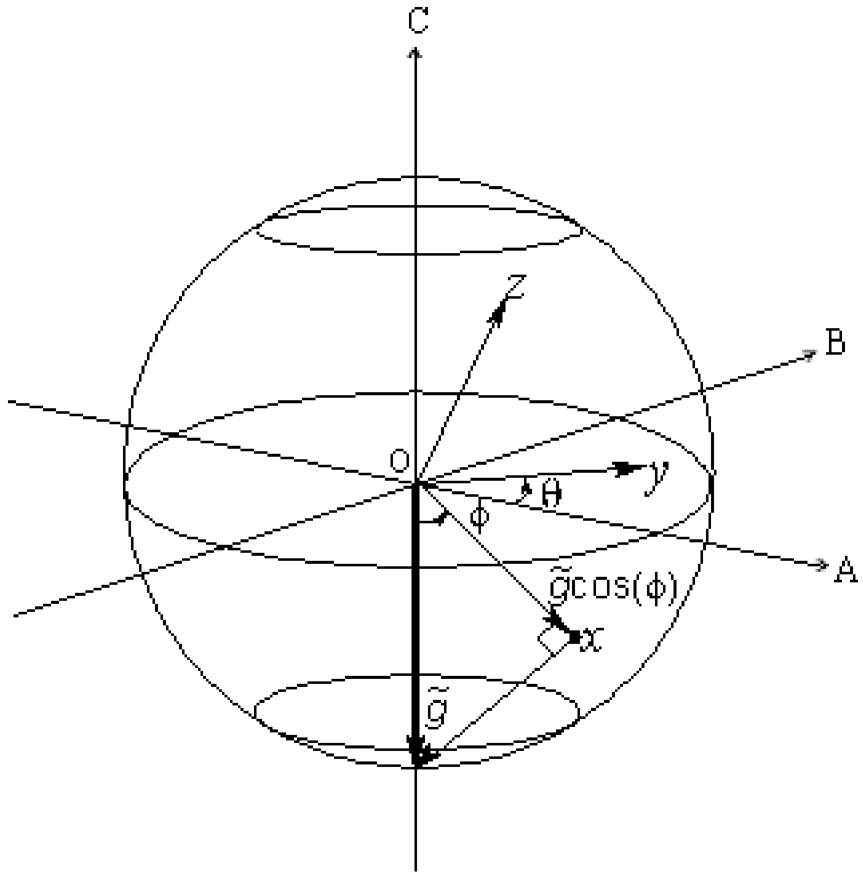


Figure 5.5: A TA is placed unmoving in a gravitational field. The TA has orthogonal axes x, y and z. The gravitational component along the x-axis of the accelerometer is given by $\tilde{g}\cos(\phi)$, where $\tilde{g}$ is the gravitational acceleration and ϕ is the angle between the $\tilde{g}$ and the sensitive axis. This is the projection of the gravitational vector onto the sensitive axis.

If a TA is used then the readings from the three axes are sufficient to determine the orientation of the device in space relative to the gravitational field, provided that the device is not moving. The vertical orientation (tilt) of a TA device can be resolved using the gravitational acceleration, but the horizontal rotation cannot be resolved. This can be seen most clearly, with reference to figure 5.5, if the TA is rotated so that its z-axis is aligned antiparallel to the gravitational vector. The output of the TA will then be $(x, y, z) \sim (0, 0, -1)$, which gives full information on the tilt angle, ϕ, but provides no information on the angle of rotation, θ. This can be seen mathematically, since for this case,

$$\phi = \arccos\left(\frac{z}{\sqrt{x^2 + y^2 + z^2}}\right) = \arccos(\frac{1}{1}) = 0, \tag{5.2}$$

but

$$\theta = \arctan(\frac{y}{x}) = \arctan(\frac{0}{0}), \text{which is not defined.} \tag{5.3}$$

The gravitational component can vary from $+1\ g$ when the accelerometer's sensitive axis is parallel to the gravitational vector, to $-1\ g$ when the accelerometer's sensitive axis is antiparallel to the gravitational vector.

Nonlinearity in the Signal

As the accelerometer is rotated in the gravitational field its output changes from $+1\ g$ to $-1\ g$ in a nonlinear manner according to equation 5.1.

The cosine curve is steepest near $\frac{\pi}{2}$ as the output passes through 0, and is flattest around 0 and π, when the output is near ± 1. This means that when the accelerometer axis is close to being in line with the gravitational vector, small changes in orientation have little effect on the signal output. For example, an alignment angle of 0° between the gravitational vector and the accelerometer axis gives an output of 1.0, while an angle of 5° gives an output of 0.996, a change of only 0.4%. In contrast, when the accelerometer axis is close to perpendicular to the gravitational vector, small changes in orientation have a large effect on the signal output. For example, an alignment angle of 90° gives an output of 0.0, while a 5° change here to 85° gives an output of 0.087, a change of 8.7%. This effect is shown in figure 5.6.

This means that when the accelerometer is vertically aligned it is less sensitive to both noise and small changes in orientation than when it is horizontally aligned.

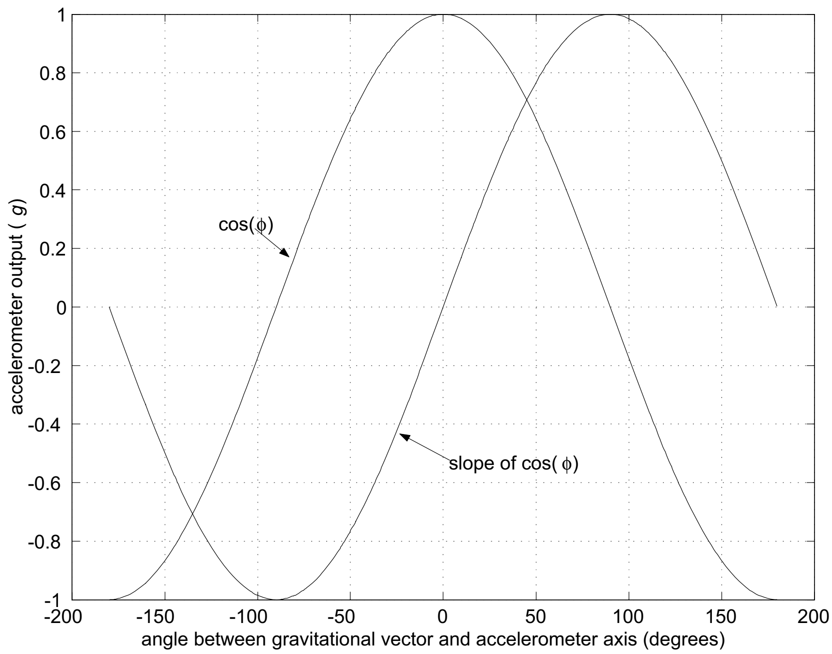


Figure 5.6: As the tilt angle of the accelerometer changes in a linear fashion, the accelerometer output changes nonlinearly along the $\cos(\phi)$ curve. The slope of the curve shows the rate of change of the accelerometer output.

Gravitational Component of Body-Fixed Accelerometers

It is possible to use the gravitational components from suitably placed accelerometers to determine the postural orientation (sitting, standing, lying, leaning, etc.) of a subject wearing the device. If the device is firmly attached to the body, and the orientation of the device relative to the subject is known then this can be used to identify the subject's postural orientation. Figure 5.7 shows the signal outputs from a TA attached at the waist for several different postural orientations. Identification of postural orientation from a waist-mounted TA is discussed in depth in section 6.6.

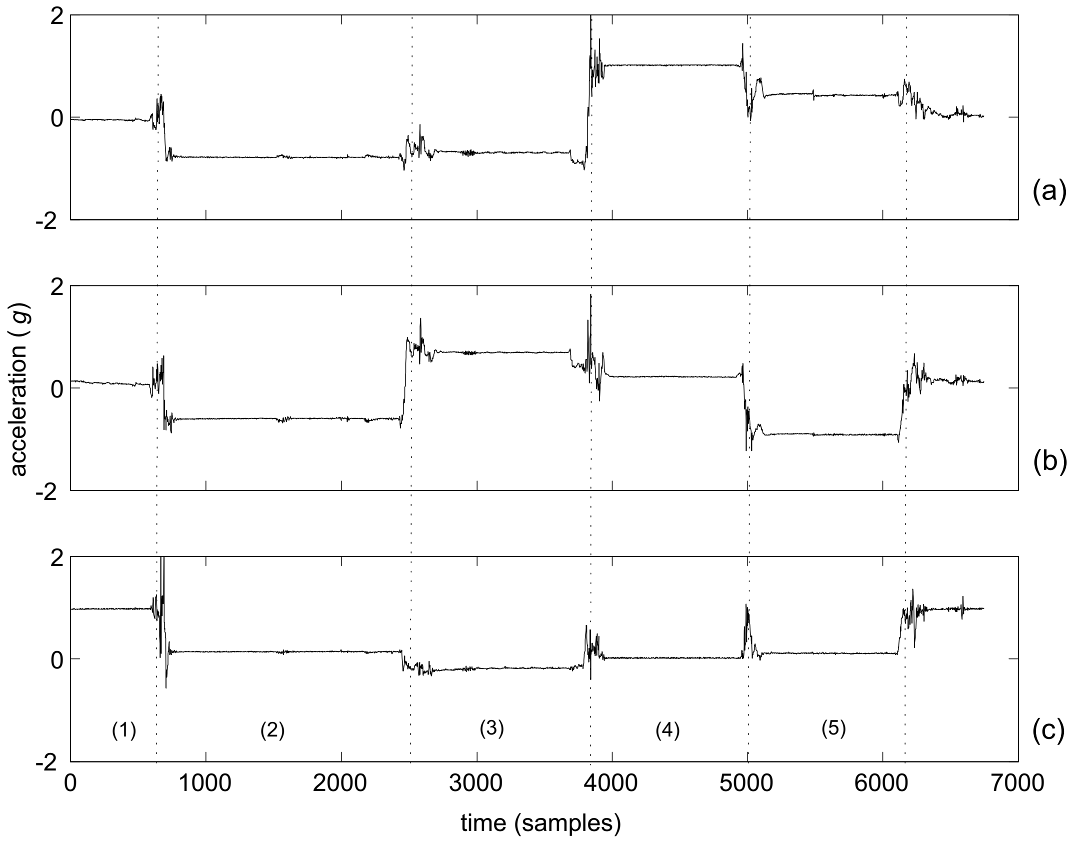


Figure 5.7: Signals obtained from a body-fixed TA while the subject was (1) standing, (2) lying supine, (3) lying left side, (4) lying face down, and (5) lying right side. The three graphs show: (a) antero-posterior acceleration, (b) medio-lateral acceleration, and (c) vertical acceleration. The TA was attached at the waist above the right anterior superior iliac spine. The dotted lines indicate the timing of changes in postural orientation.

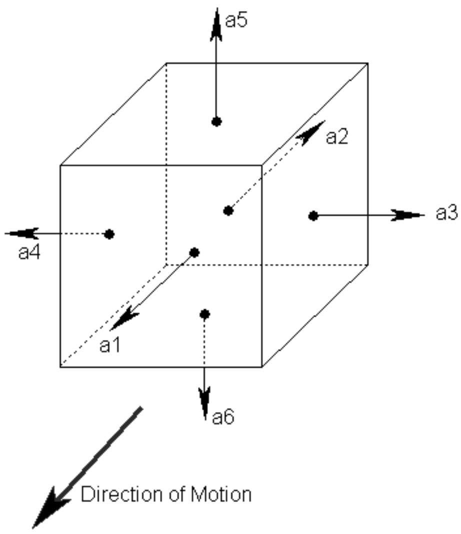


Figure 5.8: A cube with accelerometers a1 to a6 attached to each face moves along a level surface.

5.2.5 Understanding the Body Movement Component

The acceleration due to body movement is also referred to as the a.c. component or the dynamic component. These names accurately reflect the behaviour of this component: if there is no body movement, then the body acceleration component goes to zero, i.e., there is no d.c. response due to body movement. This component is referred to as the body acceleration, or BA, component in the current work. The BA component is dependent on three factors:

1. the nature of the activity being undertaken;
2. the location on the body at which the accelerations are measured; and
3. the orientation of the accelerometer relative to the body.

To illustrate, suppose that a cube moves along a surface in a straight line as follows. It begins from rest, and accelerates with uniform acceleration of $1\,\mathrm{m.\,s^{-2}}$ for $10\,\mathrm{s}$. It then continues at constant speed (acceleration $= 0$) for $10\,\mathrm{s}$ and then decelerates at the rate of $1\,\mathrm{m.\,s^{-2}}$ for the next $10\,\mathrm{s}$ after which it remains at rest. Each face of the cube has an accelerometer attached, the sensitive axis of which is mounted perpendicular to the face, and pointing out of the cube (figure 5.8).

The cube's displacement increases parabolically for the first and last $10\,\mathrm{s}$, and linearly for the middle $10\,\mathrm{s}$ (figure 5.9a). At the same time, the acceleration increases

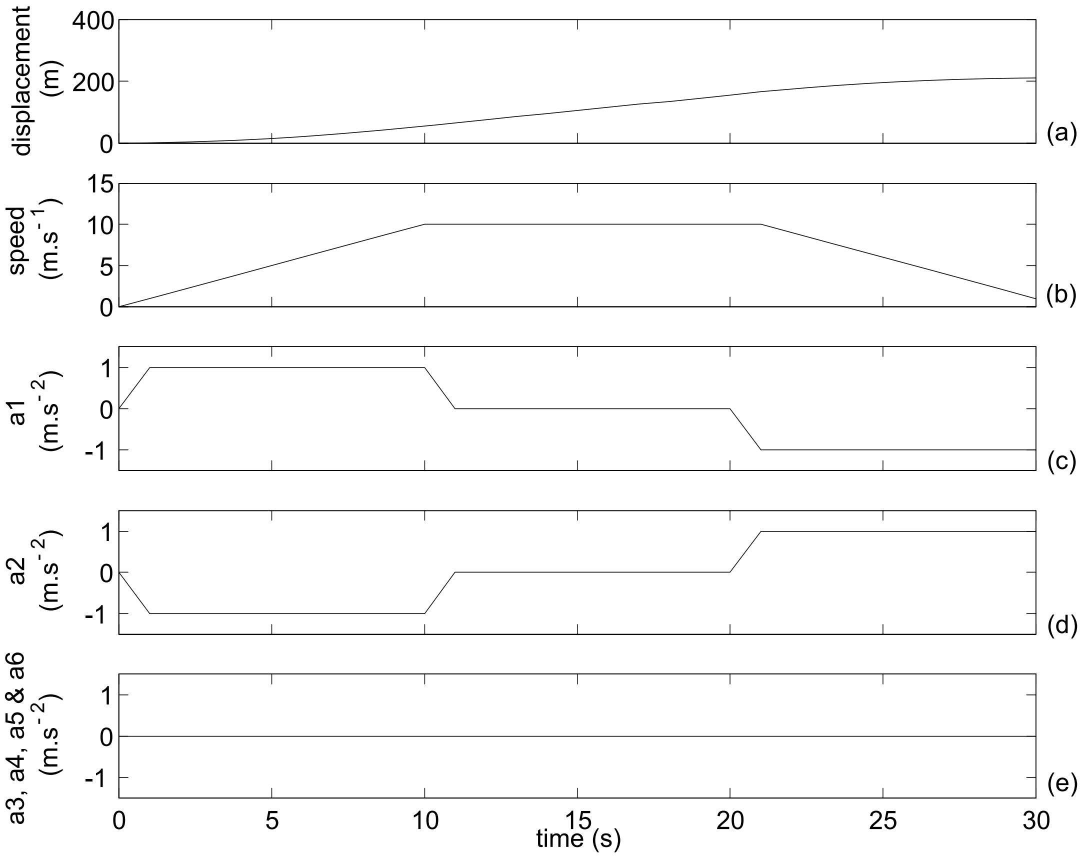


Figure 5.9: The motion of the cube and the accelerations measured by each of the six accelerometers: (a) displacement, and (b) velocity of the cube in the direction of travel. (c)-(e) show the outputs of each of the six accelerometers.

linearly for 10 s, remains steady for 10 s, and the decreases linearly to 0 m. s^{-1} (figure 5.9b). The six accelerometers record different readings. Accelerometer a1 is aligned with the direction of motion, and so records an output that is equivalent to the derivative of the velocity in the direction of travel (figure 5.9c). Accelerometer a2 is aligned opposite to the direction of motion and so records the negative of a1 (figure 5.9d). Accelerometers a3, a4, a5 and a6 are aligned perpendicular to the direction of motion and so record no acceleration due to the motion of the cube (figure 5.9e). If an accelerometer were placed on the cube such that its sensitive axis was not perpendicular to the face to which it was attached, then this accelerometer would register a component (equal to the projection of the acceleration onto the sensitive axis) of the acceleration due to the motion of the cube.

5.2.6 Understanding the Combined Signal

The resultant acceleration measured by a piezoresistive accelerometer is the vector sum of all of the accelerations acting on the device along the sensitive axis. This is equal to the gravitational acceleration component plus the body acceleration component, neglecting the effects of noise.

Thus, if x, y, and z are the outputs of the TA along the x-, y- and z-axes respectively, and if the GA component along the x-axis is represented by x_{GA}, and the BA component along the x-axis is represented by x_{BA}, and similarly for the y- and z- axes, then

$$\begin{aligned}
x &= x_{GA} + x_{BA} && (5.4)\\
y &= y_{GA} + y_{BA} && (5.5)\\
z &= z_{GA} + z_{BA} && (5.6)\\
\rho &= \sqrt{x^2 + y^2 + z^2} && (5.7)\\
&= \sqrt{(x_{GA} + x_{BA})^2 + (y_{GA} + y_{BA})^2 + (z_{GA} + z_{BA})^2}\\
&= \sqrt{(x_{GA}^2 + y_{GA}^2 + z_{GA}^2) + (x_{BA}^2 + y_{BA}^2 + z_{BA}^2) + 2\,(x_{GA}x_{BA} + y_{GA}y_{BA} + z_{GA}z_{BA})}\\
&= \sqrt{\rho_{GA} + \rho_{BA} + 2(x_{GA}x_{BA} + y_{GA}y_{BA} + z_{GA}z_{BA})} && (5.8)
\end{aligned}$$

where ρ is the acceleration magnitude vector.

5.2.7 Separating the Signal Components

The GA and BA components provide different information. The GA component provides information about the orientation of the device in space, and the BA response component provides information about the movement of the device.

When the device is not moving the GA component will register a response, but the BA component will not. If the device then undergoes a translation without rotation, the BA component will register a response but the GA component will not change its response. If the device is rotated relative to the gravitational vector both the BA and GA components will simultaneously register changing responses. All human movement contains some postural reorientation and so when the TA is worn by a person, changes in the acceleration signals are made up of simultaneous changes in the GA and BA components. This makes it difficult to identify parts of the signal as due either to BA or to GA.

Moreover, the two components have overlapping frequency spectra. The BA component ranges from above 0 Hz possibly up to 20 Hz, but is mostly contained in the range above 0 and below 3 Hz. This range overlaps that covered by the GA component, which is from 0 to several hertz.

Signal overlap between the two components is also evident in the acceleration magnitude signal, ρ (equation 5.8). ρ^2 is equal to the sum of ρ_{GA} (the acceleration magnitude of the GA component signal), ρ_{BA} (the acceleration magnitude of the BA component signal), and a cross-term between the GA and BA components.

It is possible, at least theoretically, for body movement and postural orientation variation to take place in such a way that they cancel out in the magnitude signal and no change in acceleration is registered. As an example, consider the simple case of a uniaxial accelerometer. The signal magnitude is given by

$$\rho^2 = z^2 = z_{BA}^2 + z_{GA}^2 + 2.z_{BA}.z_{GA}.$$

Suppose that there is a change of a in the BA component, and a change of d in the GA component. Then

$$\begin{aligned} \rho^2 &= (z_{BA} + a)^2 + (z_{GA} + d)^2 + 2.(z_{BA} + a).(z_{GA} + d) \\ &= z_{BA}^2 + z_{GA}^2 + 2.z_{BA}.z_{GA} + (a + d).\left((a + d) + 2.\left(z_{BA} + z_{GA}\right)\right) \end{aligned}$$

Thus, if

$$(a + d).((a + d) + 2.(z_{BA} + z_{GA})) = 0$$

that is, if

$$a = -d$$

or

$$(a + d) = -2.(z_{BA} + z_{GA})$$

then no change in acceleration will be registered by the accelerometer, even though the subject is in fact moving. This effect is caused by the interaction between the GA and BA signal components. The same effect can also theoretically occur in the three-dimensional case. This can be shown using a similar mathematical argument although the algebra becomes correspondingly more complicated.

The above reasoning shows the worst possible case in which the BA and GA components exactly cancel out. It is not possible that this could be sustained during human movement, but simultaneous change in BA and GA can be expected to lead to some degree of distortion of the resulting acceleration magnitude signal during most movements.

As there are temporal and frequency overlaps between the two components, it is not possible to perfectly separate them, and approximations must be made. This is a fundamental limitation of the technology. The first thing to note is that it may not always be necessary to explicitly separate the two components in order to obtain information. Any change in acceleration means that the subject must be moving, as postural orientation (GA component) cannot change without a nonzero BA component. Similarly, if there is no change in acceleration, it can reasonably be assumed that the subject is not moving. It also seems reasonable to assume that the changing acceleration due to body movement is much greater than the changing acceleration due to changes in postural orientation, and that the BA component generally occurs at higher frequencies than the GA component. This assumption has been implicitly made by most investigators who have needed to separate the two components ([31, 72, 76]). These investigators have achieved a separation of components using either a high-pass filter to obtain the BA component [31], or a low-pass filter to obtain the GA component [72, 76]. However, none of these papers discuss the choice of filter and no literature has been found that actually addresses this issue or discusses the quality of the filtering.

In this work, two different approaches to the problem of separating the signals were considered. Firstly, various filters were tested. Secondly, BA and GA were estimated from the magnitude acceleration, ρ.

Using Filters

The aim of filtering the signal was to approximately separate the BA and the GA components. A wide range of different types filters were tested with different characteristics and different windowing in order to determine their ability to differentiate the components of the acceleration signal. Both high pass and low pass filters were tested. When a high pass filter was used, this gave an output of BA' (an estimator of BA). GA was then estimated by $GA' = signal - BA'$. When a low pass filter was used, the output, GA', an estimator of GA, was used to derive an estimate of BA as $BA' = signal - GA'$ (figure5.10).

The filter characteristic, and impulse and step responses were produced for each filter. In order to directly compare the performance of filters, a signal consisting of a single subject sitting, standing and walking was used as a benchmark. The filters were rated on (i) the amount of BA component ripple present in GA'; and (ii) the amount of ringing in the filtered signal. The choice of filter characteristics,

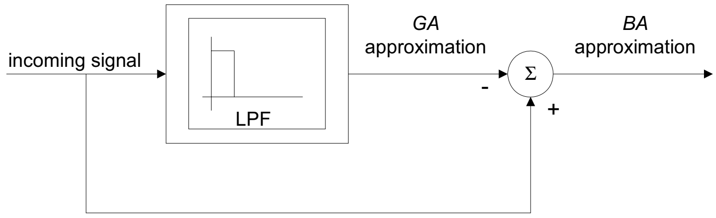


Figure 5.10: Block diagram of the separation filter.

particularly phase and impulse response can have a significant impact on signal fidelity. As a very low filter cut-off point is required (around 0.5% of the sampling rate), this can lead to substantial ringing and extended ripples in the filtered signal, or even instability in the filter.

Elliptical, bessel, butterworth, remez, chebyshev, kaiser and FIR filters were tested. The best performing filter was a custom-designed FIR filter. This was a low pass FIR filter with a 3 dB point set at 0.25 Hz and an attenuation of 50 dB/octave and exceeding 50 dB in the stop band. In contrast to filters normally used for these applications, this filter, whilst not linear phase, has a close to optimal impulse response (minimal ringing). A cut-off frequency of 0.25 Hz was chosen as it is consistent with the frequencies used by other researchers (for example, Bouten *et al.* [31] used 0.1 Hz, while Forster and Fahrenberg [76] and Fahrenberg *et al.* [72] chose to use 0.5 Hz). A cut-off frequency of 0.25 Hz represented a compromise between a filter that was realisable and a cut-off frequency that was as low as possible. The high-pass component of the signal was then obtained by subtracting the low pass filtered signal from the original signal.

Filter characteristics are shown in figure 5.11. The filter ressponses to impulse and step inputs are shown in figure 5.12, and the result of filtering on the test signal is shown in figure 5.13. This filter was stable and was able to provide a reasonable separation between the GA and BA components as can be seen from figure 5.13. The main drawback was that it still introduced some ringing into the system and this distorts the endpoints of movements. This can be a problem if the endpoints of an activity need to be accurately determined.

An alternative approach to approximating BA and GA that did not introduce any ringing was tested. This method approximated GA and BA from the magnitude acceleration, ρ.

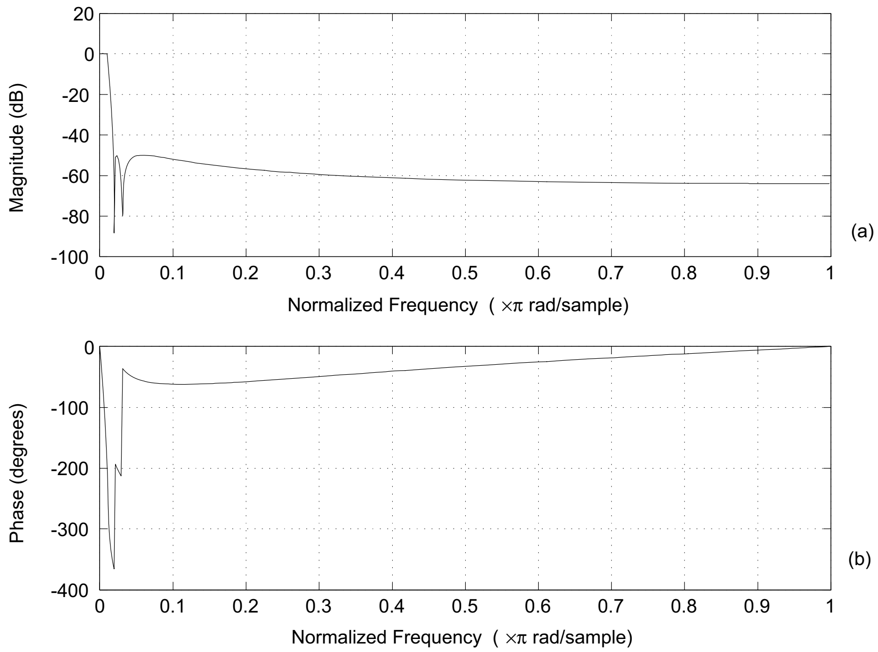


Figure 5.11: Frequency response of the discrete time FIR filter. (a) magnitude response, (b) phase response

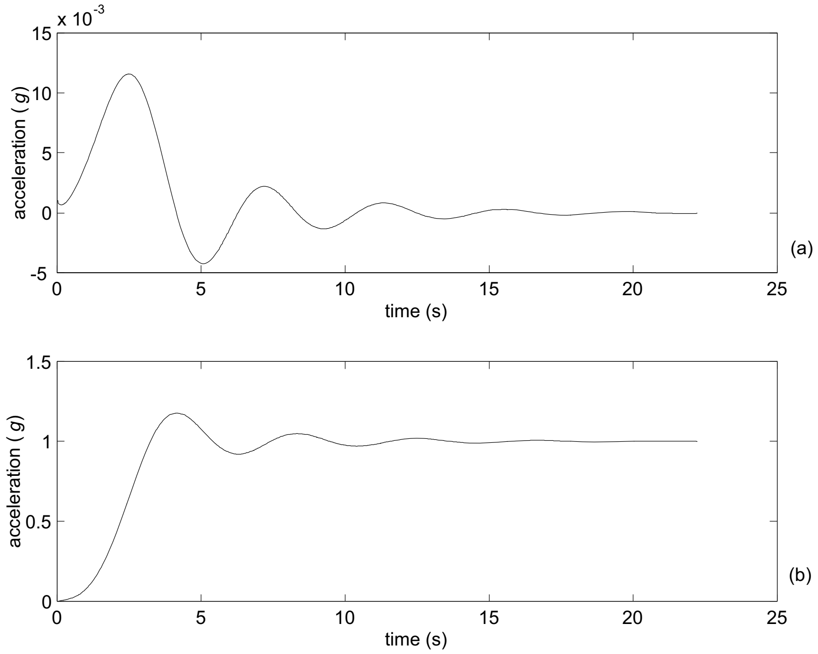


Figure 5.12: Responses of the FIR filter. (a) Impulse response, (b) step response.

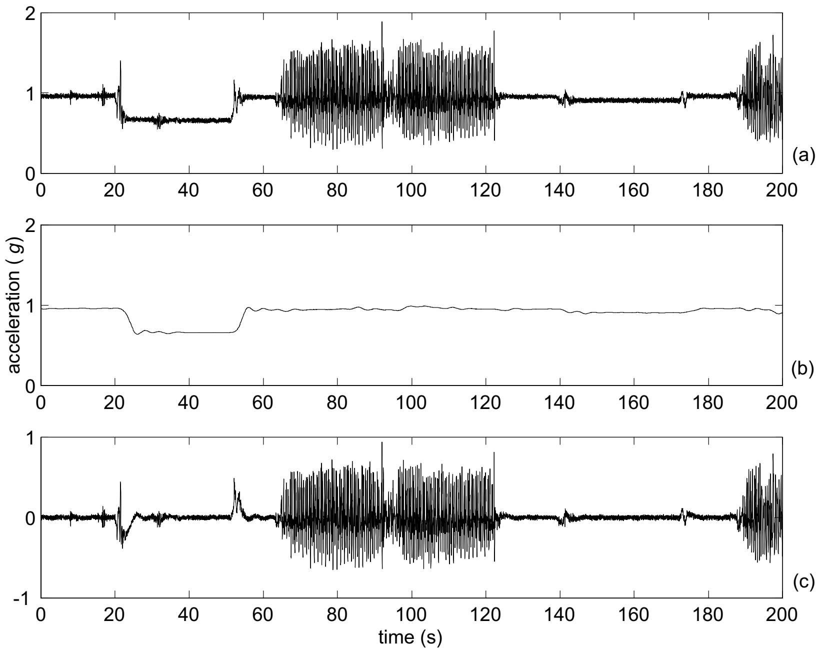


Figure 5.13: The effect of applying the FIR filter to a benchmark signal. The signal shown is the vertical acceleration component obtained from a TA attached at the waist above the anterior superior iliac spine. The subject stood, sat down, stood up, walked, stood, sat down, stood up and walked. (a) the original (composite) signal, (b) the GA estimate signal, (c) the BA estimate signal.

Using the Magnitude Acceleration, ρ

ρ is the standard magnitude vector used in the spherical coordinate representation. It can be seen from equation 5.8 that ρ is composed of ρ_{GA}, ρ_{BA} and a cross-term.

ρ_{GA}, the magnitude of the gravitational component, is equal to 1 g.

ρ_{BA} was calculated using the approximation

$$\rho_{BA}^2 \approx \rho^2 - \rho_{GA}^2, \tag{5.9}$$

or

$$\rho'_{BA} = \sqrt{\rho^2 - 1}, \tag{5.10}$$

where ρ'_{BA} is an estimator of ρ_{BA}. Here, all of the cross-term contained in ρ is attributed to the BA component. Essentially, what this method does is to remove the d.c. component from the BA component directly, without filtering.

Normally, this type of approach would not be considered because it is completely insensitive to baseline drift. It was considered here because the baseline should, at least theoretically, remain constant. Within a small region such as a house, there is no discernible change in g so there should be no change in ρ_{GA}, meaning that it can be regarded as a constant value.

The inability to allow for any variation in the d.c. offset is the main limitation of this method. It requires perfect calibration and no calibration drift. If this is not the case, then the body acceleration component estimation will contain a d.c. offset. This can lead to significant errors in calculations and algorithms that use the BA component, such as in the estimation of metabolic energy expenditure.

In order to address this, an experimentally derived estimator of the gravitational component magnitude vector, ρ'_{GA}, was computed from the signal. The TA was placed, unmoving, on a table for several minutes. ρ'_{GA} was calculated as

$$\rho'_{GA} = \sqrt{\frac{1}{N}\sum_{1}^{N}(x^2 + y^2 + z^2)} \tag{5.11}$$

where N was the number of samples that were recorded. ρ'_{BA} was then calculated using equation 5.10.

The test signal shown in figure 5.13(a) was used to evaluate the performance of the separation. The use of ρ'_{GA} led to improved results in the sense of a reduction in d.c. offset in the body acceleration component estimate, compared to using $\rho_{GA} = 1$, but the approximation is still highly dependent on the accuracy of calibration, and lacks robustness.

When using estimator ρ'_{BA}, the error in ρ_{BA} increases with a squared relationship to the error in ρ'_{GA}. A second estimator of ρ_{BA} was considered in which the error in ρ'_{BA} increases linearly with the error in ρ'_{GA}. This estimator was

$$\rho''_{BA} = \rho - \rho'_{GA}. \tag{5.12}$$

Although this estimator is not obviously derived from the definition of ρ as is the first one, it serves an identical function in that it aims to remove the d.c. offset from ρ_{BA} without filtering. When applied to the test signal, ρ''_{BA} proved to be a better estimator than ρ'_{BA}, and when the system was well-calibrated it gave better results than the filtering methods because it left no ringing and successfully removed all of the d.c. component from ρ_{BA}. Nonetheless, this method still lacks robustness against errors in ρ'_{GA}. If the TA was not perfectly calibrated (and an error of less than 1% was sufficient), then changing the orientation of the device introduced error into ρ'_{GA}, and in less well controlled conditions this led to a significantly large d.c. offset in ρ_{BA}.

A third estimator was considered that used splines to estimate ρ_{GA} from the signal. This method allowed the estimate of ρ_{GA} to vary over time, making it more robust to inexact calibration and calibration drift. During periods of rest, ρ''_{GA} was estimated by averaging over the period of rest. During periods of activity, ρ''_{GA} was allowed to change linearly with time. Its starting value was the value attributed to it in the preceding rest period, and its finishing value was the value attributed to it in the succeeding rest period. This approach gave a much smaller d.c. offset in ρ_{BA} than the other approaches when there was a small calibration error, but it still had the same robustness limitations to larger calibration errors as the other acceleration magnitude methods.

Despite the robustness limitations, all of these magnitude acceleration methods have the advantage that they introduce no distortion into the signal, and in particular, activity endpoints in the signal remain unaffected by the separation process.

Conclusion

Two different approaches were applied to separate the signal components. The first method involved filtering the signal using a low cutoff frequency. The best filter was found to be a high pass FIR filter that had an optimised impulse response to minimise ringing. The main drawback was that it did still introduce some ringing into the system.

This limitation could be overcome by using approximation methods based on the acceleration magnitude, ρ. The best of these methods estimated the body acceleration component magnitude as $\rho_{BA} \approx \rho - \rho_{GA}$. This worked best when a spline method was used to estimate ρ_{GA}, although introducing splines added an order of computational complexity to the system over using a simple constant value. These methods have the limitation that they cannot guarantee the removal of the d.c. component from the body acceleration estimate and this can be a significant problem for calculations and algorithms that require a signal without a d.c. offset when there is no body movement.

Neither of these two methods is clearly superior to the other. The preferred approach depends on the context in which it is to be applied. In some instances, such as the estimation of metabolic energy expenditure, it is necessary to extract only the body acceleration component, and it is necessary for the acceleration to have no d.c. offset when the TA is not moving. In this circumstance, filtering is the preferred option. On the other hand, in endpoint detection, distortion of the activity endpoints through the introduction of ringing is a more significant problem than the introduction of a slight d.c. offset so in this case, approximating the body acceleration component from the acceleration magnitude signal is preferable. However, the difficulties in separating the two components make it preferable not to attempt the separation if it is not required, but rather to develop algorithms that can use the combined signal.

5.2.8 Summary

This section described the composition of the TA signal. Each of the signal components was studied from basic principles. The signal consists of a body acceleration (BA) component, a gravitational acceleration (GA) component, and noise. The amount of noise intrinsic to the system is small (approximately 4.3×10^{-3} g r.m.s.) and although the RF transmission is susceptible to noise, this can be reduced by median filtering techniques. The gravitational component provides information on the tilt angle of the TA device which can be used to make inferences about the postural orientation of a subject when the device is worn. The body acceleration component provides information on the movement of the subject. These two components are linearly combined in the TA signal and as they overlap both in time and in frequency, they cannot be easily separated, although approximations to the two components can be made.

5.3 Representation of the TA Signal

5.3.1 Introduction

The TA signal contains a range of information. Different signal representations accentuate different aspects of this information. The data can be represented in its raw, Cartesian form by three orthogonal accelerations, or it can be represented in spherical coordinates by a magnitude and two angles. Although isomorphic, the two representations present the information differently and so are each useful on different occasions.

As acceleration is the derivative of velocity and the second derivative of displacement, the acceleration signal can also be integrated to obtain measures of velocity and displacement. However, the heterogenous composition of the acceleration signal precludes these from providing meaningful measures of the movements of a subject wearing the device.

5.3.2 Cartesian or Spherical Signal Representation?

The data are provided from the TA in a Cartesian form where the overall acceleration vector is represented by its three orthogonal components (x, y, z). The data could also be represented in spherical coordinates (ρ, ϕ, θ), where ρ is the magnitude vector, ϕ is the tilt angle from the vertical z-axis to the horizontal x-y plane and θ is the angle of rotation from the x-axis to the y-axis (figure 5.5). The following equations are used to transform between Cartesian and spherical representations:

$$x = \rho\cos(\theta)\sin(\phi) \tag{5.13}$$

$$y = \rho\sin(\theta)\cos(\phi) \tag{5.14}$$

$$z = \rho\cos(\phi) \tag{5.15}$$

$$\rho^2 = x^2 + y^2 + z^2 \tag{5.16}$$

$$\tan(\theta) = \frac{y}{x} \tag{5.17}$$

$$\cos(\phi) = \frac{z}{\rho} \tag{5.18}$$

The choice of whether to use a Cartesian or a spherical representation depends on the application. If a subject wears the TA at the waist and is upright, with the z-axis vertically aligned then the angle of rotation, θ, is numerically unreliable as it involves division by a very small amount. ϕ, on the other hand, can provide information on the angle of inclination of the subject. ρ provides movement information in a one-dimensional form, but as was noted in section 5.2.7, movement can be distorted in ρ because of interaction between the body acceleration and gravitational acceleration components. Both Cartesian and spherical representations are employed in the current work

5.3.3 Integration of the Signal to Obtain Displacement and Velocity

Theoretically, the acceleration signal should be able to be integrated to give velocity, and the velocity signal integrated to yield displacement. However, there are difficulties in achieving this in practice. Evans *et al.* [70] wrote that "a well recognised difficulty with the use of accelerometers in gait analysis has been the noise problem when acceleration is measured and then integrated to determine velocity and position". The main problem in integrating to obtain velocity and displacement is the gravitational component of the signal, which results in a d.c. offset in the acceleration signal. An offset of 0.1 g is equivalent to an acceleration of just below $1\,\mathrm{m\,s^{-2}}$. Over a period of 1 s, this leads to an error in displacement of 1 m. Over a period of 10 s, this leads to an error in displacement of 100 m! The problem, then, with double-integration is that the system is very sensitive to any d.c. offset that is present in the acceleration signal, and these d.c. offsets are present due to the gravitational signal component.

For double integration to give a true displacement signal, only the body acceleration component should be included. However, as discussed, this cannot be perfectly extracted from the TA signal and so there will always be error in the body acceleration component estimate that will confound attempts to derive a measure of change in displacement.

This effect was observed in a study in which velocity and displacement measurements were derived from the acceleration signal produced by the TA.

Experimental Procedure

Three tests were undertaken using the TA unit. In all of the tests, only the vertical acceleration component was considered. In the first test, the TA unit was held by the investigator, and placed against a vertical corner join of two walls so that it could only be moved in one dimension. The TA unit was moved along the corner join with varying accelerations. It was moved vertically upwards 10 times, and vertically downward 10 times. In each case, the displacement was 60 cm. In this test, the orientation of the TA unit was fixed, and as a result the GA signal component was constant.

In the second test, the TA unit was held by the investigator in free space. The unit was moved upwards and then downwards with a displacement of 1 m. This test was repeated ten times. In the third test, the TA unit was worn above the anterior superior iliac spine of a subject who performed 10 sit-to-stand and 10 stand-to-sit transitions.

Data Analysis

Each of the vertical component signals was median filtered to remove noise spikes. Velocity and displacement estimators were obtained as follows. The signal was filtered using the FIR filter described in section 5.2.7 to obtain an estimate of the BA signal component. The signal was then integrated to obtain a measure of velocity, and integrated again to obtain a measure of displacement.

Results

In the first test, the direction of displacement was correctly identified in every case by the sign of the displacement. However, the magnitude of the displacement was not accurately measured (mean estimated displacement 0.23 ± 0.1 m standard deviation).

In the second test, the direction of displacement was correctly identified in 18 of the 20 trials. The magnitude of the displacement was not accurately identified and there was a greater standard deviation in the estimates of displacement (0.5 ± 0.3 m).

In the third test, the direction of displacement was only correctly identified half of the time.

Discussion and Conclusion

When the TA unit was moved in such a way that there was no alteration in orientation during the movement, double integrating was able to identify the direction of the movement. However, even a small amount of change in orientation added sufficient error to the system to make the results of the double integration an unreliable indicator of displacement direction. In the case of the sit-to-stand and stand-to-sit transitions, when movement was nonlinear and had six degrees of freedom, the estimate of displacement was so inaccurate that it could not even provide any information on the direction of the movement!

There were two factors contributing to the error in the estimate of displacement in the first test. The first was the intrinsic noise in the system. An r.m.s. noise level of 6.6×10^{-3} g leads to a potential error of $6.6 \times 9.81 \times 10^{-3}\,\mathrm{m.s^{-2}} \times 1\,\mathrm{s} = 65\,\mathrm{mm}$ each second, and the peak noise level of 25×10^{-3} g leads to a potential error of $25 \times 9.81 \times 10^{-3}\,\mathrm{m.s^{-2}} \times 1\,\mathrm{s} = 245\,\mathrm{mm}$ each second. The second contributing factor was the error introduced by the low pass filter used to separate the body movement acceleration from the gravitational acceleration. In the second and third tests, the presence of acceleration due to the gravitational component in the body acceleration component signal estimate was the main cause of inaccuracy.

It is evident that the acceleration signal cannot be integrated to obtain meaningful information on velocity or displacement due to the presence of the gravitational signal component and noise in the signal.

5.3.4 Summary

The signal from the TA is received in Cartesian form, which provides the information in terms of the net acceleration acting along each of the three orthogonal axes. It can be transformed to an isomorphic spherical coordinate form, from which the net acceleration magnitude and the vertical tilt angle can be more easily identified.

The acceleration signal cannot be integrated to determine the velocity and displacement of motion due to the presence of the gravitational acceleration component and noise in the signal.

5.4 Understanding the Effect of Device Placement on the Signal

5.4.1 Introduction

The signal obtained from a TA worn by a person is dependent upon its placement. Even if the TA unit is designed to be worn in one particular position, the exact attachment location will vary across subjects due to differences in body shape. The placement location and orientation may also vary for the same subject from day-to-day, depending on the subject's choice of clothing. The purpose of this section is to gain an understanding of the effect of TA placement on the output acceleration signals.

5.4.2 An "Ideal" Subject

Consider the case of a TA attached to a rectangular prism within a global coordinate system (figure 5.14). The global coordinate system has axes X_g, Y_g and Z_g and is left handed. Its origin, O, is located at the centre of the prism. The rectangular prism is placed so that the X_g-axis runs from the origin through the centre of the front face of the prism, the Y_g-axis runs from the origin through the left face (as seen by the prism), and the Z_g-axis runs from the origin through the bottom face. The gravitational vector, g, is parallel to the Z_g axis. Associated with the prism is a coordinate system, which is also centred at O, and which has axes X_p, Y_p and Z_p that are aligned with X_g, Y_g and Z_g respectively when the prism is resting on its bottom face. The TA has coordinate axes x, y and z. It is placed on the front face of the prism in such a way that its x, y and z axes are aligned with the X_p, Y_p and Z_p axes respectively. In this situation, the TA output will be given by the vector $(x, y, z) \sim (0, 0, 1)$.

The output of the TA is dependent on the postural orientation of the prism and on the placement and orientation of the TA relative to the prism. The TA output vector is the component of g acting along each of the axes of the TA. Since the gravitational component is known in the global coordinate system, the TA output vector can be determined by first computing the coordinate transformation matrix between the TA coordinate system and the global coordinate system and then multiplying the base vector of $(0, 0, 1)^T$ by this matrix.

As an example, consider the situation illustrated in figure 5.15 in which the prism is resting on its left face and the TA is attached to the right face of the prism,

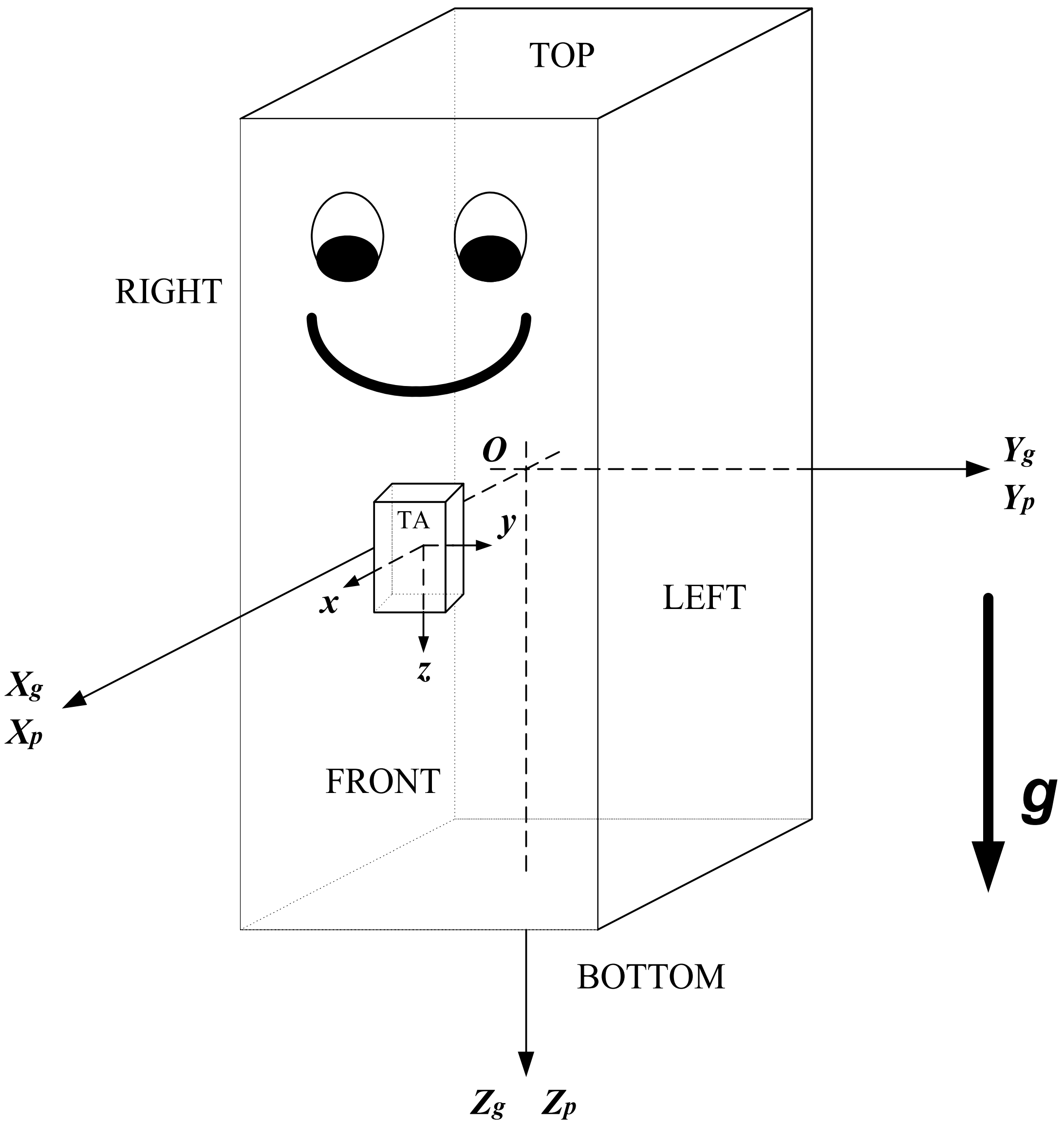


Figure 5.14: Ideal case of a rectangular prism with a TA attached to the front face.

with the x-axis aligned with the $-Y_p$-axis, the y-axis aligned with the Z_p-axis, and the z-axis aligned with the $-X_p$-axis.

Figure 5.16 shows the coordinate transformations that occur due to the reorientation of the prism, the new placement of the TA, and the reorientation of the TA. It can be seen that for this example, the coordinate transformations are $x \leftrightarrow -Z_g$, $y \leftrightarrow -Y_g$, and $z \leftrightarrow -X_g$, leading to a transformation matrix of

$$R_M = \begin{bmatrix} 0 & 0 & -1 \\ 0 & -1 & 0 \\ -1 & 0 & 0 \end{bmatrix}.$$

R_M can also be computed by multiplying together the rotation matrices from each of the three steps:

$$\begin{aligned}
R_M &= R_1 \times R_2 \times R_3, \text{ where} \\
R_1 &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(270^\circ) & -\sin(270^\circ) \\ 0 & \sin(270^\circ) & \cos(270^\circ) \end{bmatrix} \\
R_2 &= \begin{bmatrix} \cos(90^\circ) & -\sin(90^\circ) & 0 \\ \sin(90^\circ) & \cos(90^\circ) & 0 \\ 0 & 0 & 1 \end{bmatrix} \\
R_3 &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(270^\circ) & -\sin(270^\circ) \\ 0 & \sin(270^\circ) & \cos(270^\circ) \end{bmatrix}
\end{aligned}$$

The resulting TA output for this situation is $(-1, 0, 0)$.

The rectangular prism provides a simple geometry from which to determine the behaviour of the TA under static conditions. However, the waist of a human subject is not well-modelled by a rectangle as few humans have waists with four sharp corners! Consider next a cylinder. In this geometry, the waist of the subject is modelled by a smooth curve (figure 5.17). The placement of the TA is identified by the angle of placement, t. This angle measures the angular distance from the centre of the back. In the rectangular prism model, there were only four possible placements on the sides of the prism. These were on the back, left, front and right faces. On the cylinder, however, there is a continuum of placements on the curved face. Placements at the back, left, front and right correspond to $t = 0^\circ$, 90°, 180°, and 270° respectively.

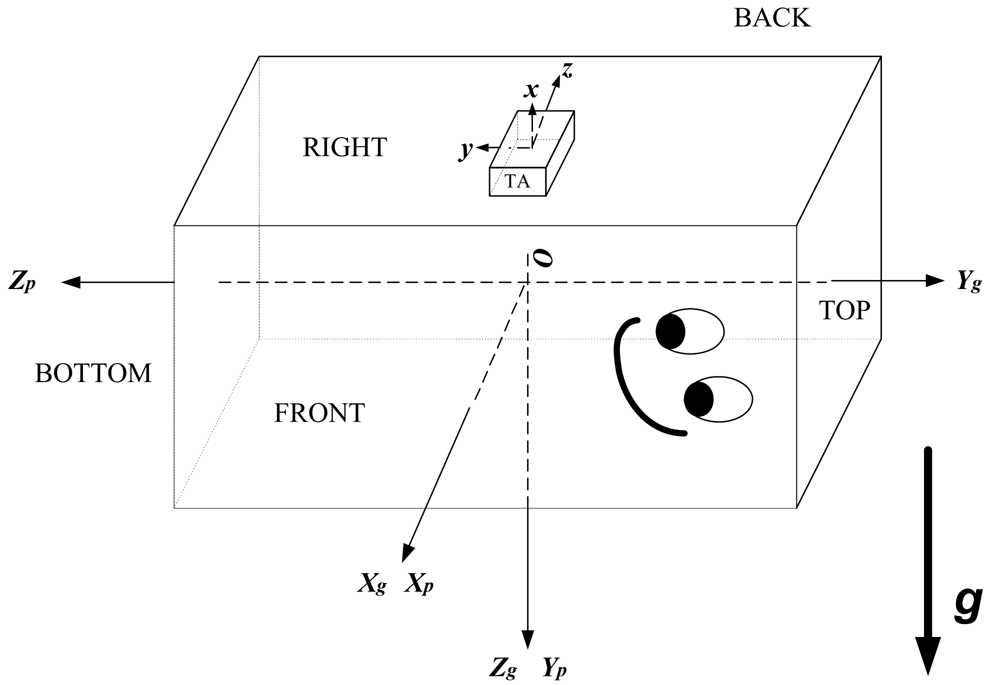


Figure 5.15: The rectangular prism with the TA moved to the right face and rotated through 270°. The prism is resting on its left face. The TA output vector is $(-1, 0, 0)^T$.

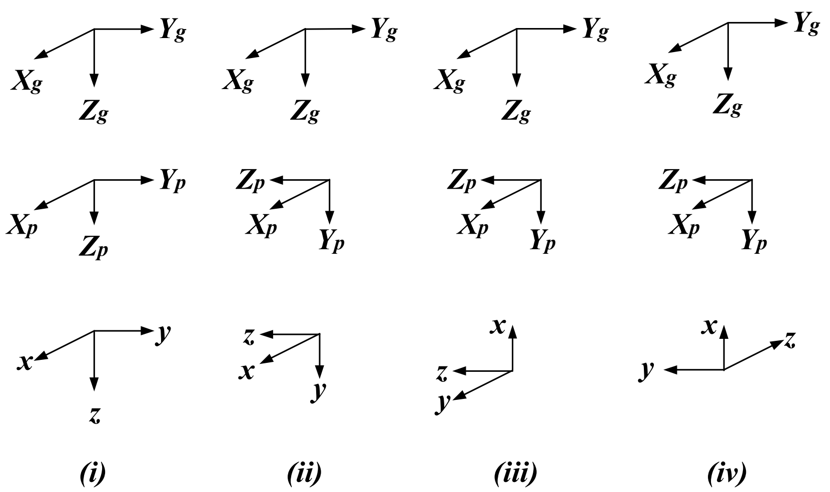


Figure 5.16: Sequence of coordinate transformations for the example of figure 5.15. (i) Prism upright, with TA attached to front face, as shown in figure 5.14, (ii) prism rotated to rest on left face, (iii) TA moved to right face, and (iv) TA rotated to new orientation.

The model can be further enhanced by using an elliptical cylinder with an extended medio-lateral axis and a squashed antero-posterior axis. Table 5.3 lists the TA outputs when the TA is attached to the face of a rectangular prism and to the face of a cylinder with $t = 225°$. The fourth row of the table gives the signal outputs for a TA attached at $t = 225°$ between the front and the right side of an elliptical cylinder with a major axis to minor axis ratio of 30 : 23, a typical ratio for the waist of a human subject.

When the TA is attached to the rectangular prism such that its axes are aligned parallel to the axes of the prism the outputs can only take values of -1, 0 and $+1$ since each of the axes must either be aligned parallel, antiparallel, or perpendicular to Z_g. When the TA is attached to the cylinder, the axes can be aligned at any angle relative to Z_g and so the three axis outputs can range between -1 and $+1$. The TA output is also affected by the shape of the ellipse. In the regular cylinder, the points at which the x- and y-axis values have the same magnitude (0.71) when the cylinder is lying face-down are equally spaced at $t = 45°$, 135°, 225°, and 315°. As the ratio length:breadth increases, the angles of placement at which the x- and y-axis values have the same magnitude when the cylinder is lying face-down shift towards the left and right sides of the prism, that is, they move towards $t = 90°$ and 270°. For the cylinder with a length:breadth ratio of 30 : 23 they occur at $t = 52.52°, 127.48°, 232.52°$ and 307.47°.

The rectangular prism, the regular cylinder and the elliptical cylinder are simple models of an "ideal" subject. When the geometry of the subject is known and the subject is stationary, then the output of the TA can be deterministically calculated given:

1. the subject's postural orientation;

2. the location at which the device is placed on the subject; and

3. the orientation of the TA relative to the subject.

The following study investigates the goodness of fit of these models to data obtained from real subjects.

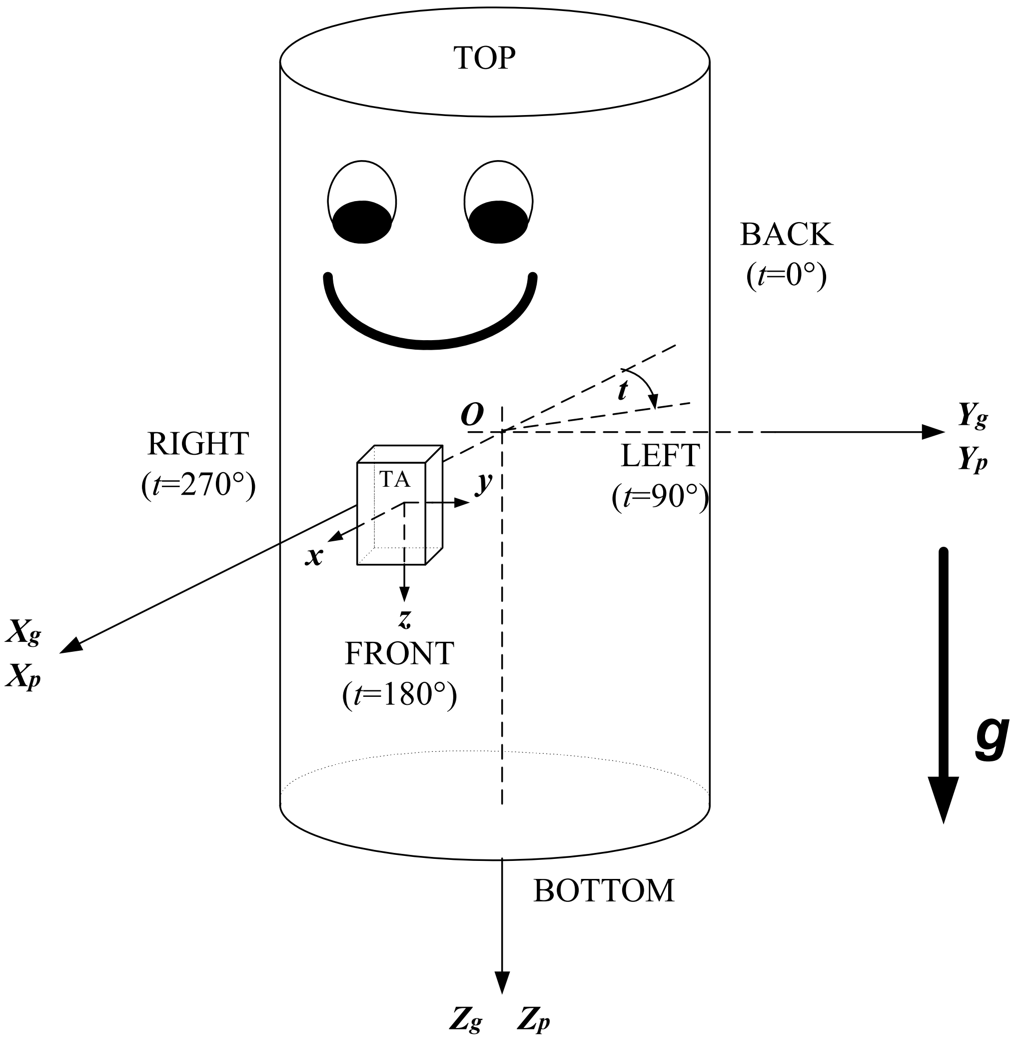


Figure 5.17: Ideal case of a cylinder with a TA attached. The axes of the TA are aligned with the axes of the cylinder.

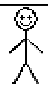
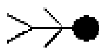
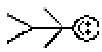
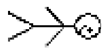
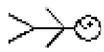
	 standing upright	 standing on head	 lying face down	 lying supine	 lying left side	 lying right side
attached to front face of rectangular prism, z-axis parallel to vertical edge, +ve down	$\begin{pmatrix}0\\0\\1\end{pmatrix}$	$\begin{pmatrix}0\\0\\-1\end{pmatrix}$	$\begin{pmatrix}1\\0\\0\end{pmatrix}$	$\begin{pmatrix}-1\\0\\0\end{pmatrix}$	$\begin{pmatrix}0\\1\\0\end{pmatrix}$	$\begin{pmatrix}0\\-1\\0\end{pmatrix}$
attached to right face of rectangular prism, z-axis parallel to vertical edge, +ve down	$\begin{pmatrix}0\\0\\1\end{pmatrix}$	$\begin{pmatrix}0\\0\\-1\end{pmatrix}$	$\begin{pmatrix}0\\1\\0\end{pmatrix}$	$\begin{pmatrix}0\\-1\\0\end{pmatrix}$	$\begin{pmatrix}-1\\0\\0\end{pmatrix}$	$\begin{pmatrix}1\\0\\0\end{pmatrix}$
attached to cylinder at $t = -135°$, z-axis parallel to vertical edge, +ve down	$\begin{pmatrix}0\\0\\1\end{pmatrix}$	$\begin{pmatrix}0\\0\\-1\end{pmatrix}$	$\begin{pmatrix}.71\\.71\\0\end{pmatrix}$	$\begin{pmatrix}-.71\\-.71\\0\end{pmatrix}$	$\begin{pmatrix}-.71\\.71\\0\end{pmatrix}$	$\begin{pmatrix}.71\\-.71\\0\end{pmatrix}$
attached to elliptical cylinder (a=15cm, b=11.5cm) at $t = -135°$, z-axis parallel to vertical edge, +ve down	$\begin{pmatrix}0\\0\\1\end{pmatrix}$	$\begin{pmatrix}0\\0\\-1\end{pmatrix}$	$\begin{pmatrix}.79\\.61\\0\end{pmatrix}$	$\begin{pmatrix}-.79\\-.61\\0\end{pmatrix}$	$\begin{pmatrix}-.61\\.79\\0\end{pmatrix}$	$\begin{pmatrix}.61\\-.79\\0\end{pmatrix}$

Table 5.3: TA output for 6 basic postural orientations when the TA is placed at various positions on a prism and a cylinder.

5.4.3 A Study of the Effect of Device Placement on Signals Obtained During Rest

Introduction

As shown in section 5.4.2, the relationship between the signals produced by the TA and the postural orientation of the subject is dependent on the placement of the TA. Real subjects have a far more complicated geometry than the simple cases expounded in the previous section, and this geometry differs for every person. Moreover, human subjects are not rigid bodies and there are torsional and displacement forces that act on the body to cause deflection and distortion. In addition, the exact orientation of the TA unit will depend on the placement location, the body shape of the wearer, and on the clothing to which the device is attached and will vary from person-to-person, and for the same person on different occasions. As the interpretation of TA signals becomes less clear-cut it becomes important to understand the effect of positioning and orientation on the resultant signals from the body-fixed triaxial accelerometer.

The primary aim of this study was to develop a general method for identifying postural orientation from the signals received from a waist-mounted triaxial accelerometer (TA). Investigations were made in order to determine a relationship between (i) the placement of a waist-mounted TA; (ii) the postural orientation of a stationary subject; and (iii) the signals produced by the accelerometer. A deterministic approach was adopted in which the geometry of the subject was modelled using simple geometric figures and these were used to predict the TA output signals. Data were collected from a cohort of subjects and the experimental TA outputs were compared to the predicted TA outputs to obtain a measure of the quality of the models.

Experimental Procedure

Twenty three normal, healthy subjects participated in the study (7 female, 16 male; age 30.5 ± 6.3 years (mean $\pm$ standard deviation); height 174.3 ± 9.7 cm; weight 72.3 ± 11.3 kg; body mass index $23.7 \pm 2.4\,\mathrm{kg.\,m^{-2}}$). Each subject was tested in a 30 minute session.

The circumference of the subject's waist was measured using a tape measure. The length of the medio-lateral axis at the waist (l_x) and the length of the antero-posterior axis at the waist (l_y) were measured using a pair of callipers.

Data were collected while the subjects were standing or lying supine with the TA

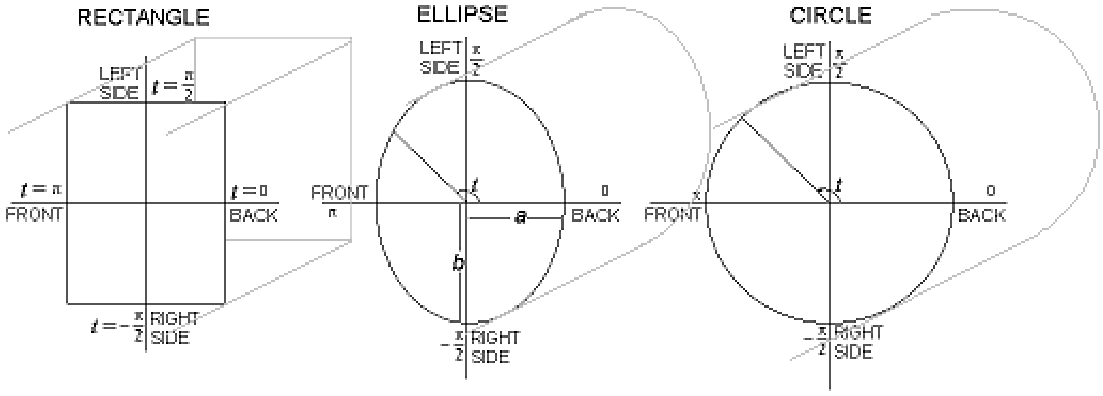


Figure 5.18: Horizontal cross-sectional models of the waist. (a) rectangle, (b) ellipse, and (c) circle.

attached at six different positions around the waist. The attachment positions were (i) on the right side; (ii) at the front-right, above the right anterior superior iliac spine; (iii) at the front in the middle; (iv) at the front-left, above the left anterior superior iliac spine; (v) on the left side; and (vi) at the back in the middle.

The subject was shown how to attach the TA device and then asked to attach it at the first attachment position. No special belt or clothing was used, so the attachment point varied slightly across subjects. Subjects wearing a belt clipped the device onto the belt, while subjects wearing trousers or a skirt without a belt attached the device directly to the clothing. The subject was asked to stand still and data were collected for 20 s. The subject was then asked to move the TA to the second attachment placement and data was collected for 20 s while the subject was standing. This procedure was repeated for the four remaining placements.

Following this, the subject was asked to lie supine, and 20 s of data were collected with the TA attached at each of the same six placements.

Data Analysis

Model Development The subjects were modelled by a number of simple geometries that would allow prediction of the TA output for a given position and postural orientation. The horizontal cross-section of the subjects at the waist was modelled as (i) a rectangle, (ii) an ellipse and (iii) a circle. These are shown diagrammatically in figure 5.18.

These horizontal cross sections were built into three-dimensional surfaces to model the surface of the subject near the waist. Uniform and uniformly tapered models were considered. The uniform models assumed that the horizontal cross sections above and below the waist were the same as those at the waist. The models tested under this assumption were the rectangular prism, the elliptical cylinder and the regular cylinder.

The prismatic models focused on the horizontal cross-sectional geometry of the waist but ignored any offset from the vertical in the z-axis by making the assumption that the vertical axis of the TA is directly aligned with the vertical axis of the subject. This meant that when the subject was standing, the predicted TA output vector was $(x, y, z) = (0, 0, +1)\ g$ regardless of where on the waist the device was positioned. When the subject was lying, the predicted z-axis vector component was zero and the horizontal cross-sectional model defined the values of the x- and y-axis components.

Rectangular Prism Model: The rectangular prism was the simplest model investigated. The TA was positioned on the face of the prism such that its axes were aligned with the faces of the prism. As the prism lay on each of its six faces, one of the accelerometer axes measured $\pm 1\ g$, and the other two axes recorded zero acceleration (refer to section 5.4.2). This model allowed the postural orientation of the subject to be classified as one of six discrete states.

Elliptical Cylinder Model: The second model used was an elliptical cylinder. The major axis of the ellipse represented the medio-lateral axis of the subject, and the minor axis represented the antero-posterior axis. These were described by two subject-dependent parameters, a and b, which represented half the lengths of the minor and major axes respectively, i.e. $l_x = 2b$ and $l_y = 2a$.

With reference to figure 5.18b, the device position on the waist can be described in parametric form as $(x, y) = (a\cos(t), b\sin(t))$ where t is the angle from the centre of the back, proceeding around the body toward the left side. The centre of the ellipse represented the approximate centre of gravity of the body, and the circumference of the ellipse represented the circumference of the horizontal cross section of the body at the waist. When the subject was lying supine, the value of the output vector was given by $(gx, gy, gz) = g(-\sin\theta, \cos\theta, 0)$, where $\theta = \arctan\left(\frac{b\cos t}{a\sin t}\right)$. Again, the z-axis of the TA was assumed to be parallel with the vertical axis of the subject.

Circular Model: The third model that was considered was a regular cylinder. This model was a special case of the elliptical cylinder model. It was identical to the elliptical cylinder model when $a = b$, and hence $\theta = t$. This meant that the regular cylinder had no subject-dependent parameters and hence constituted a simpler model than the elliptical cylinder.

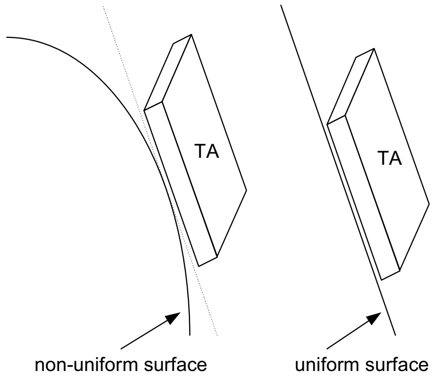


Figure 5.19: Attachment of the TA unit to a non-uniform surface can be represented by attachment to a uniform surface where the tangent to the non-uniform surface at the point of attachment is used as the uniform surface.

Two assumptions were made in all of these uniform models. Firstly, all upright orientations had the TA z-axis parallel to g, i.e. $(x, y, z) = (0, 0, 1)\ g$ and the angle between the gravitational vector and the TA z-axis, ϕ, was $0°$. Secondly, all lying orientations had the z-axis was perpendicular to g, i.e. $(x, y, z) = (x, y, 0)\ g$ and angle $\phi = 90°$.

In order to test the validity of these assumptions, models with uniform tapering were also considered. In these models, the surface of the shape at the waist was not parallel to g when upright, nor perpendicular to g when lying. Uniform tapering was used because attachment of the TA to a non-uniform surface can be represented by attachment of the TA to a uniform surface where the tangent to the non-uniform surface at the point of attachment is used as the uniform surface. This is illustrated in figure 5.19.

Three basic types of vertical axis modelling were considered for each horizontal cross-section. These were the prismatic model (without tapering), and tapered models in which the apex was in the direction of the head and in the direction of the feet. These are shown in figure 5.20 for the elliptical cross section. The angle, ψ, of the cone or prism was defined as the arctangent of the ratio of the height (h) to the width (w). Changing this angle changed the slope of the shape, and hence the amount of deviation from $(x, y, z) = (0, 0, 1)\ g$ when standing and $(x, y, z) = (x, y, 0)\ g$ when lying.

In applying the tapered models, it was assumed that the vertical axis of the model, Z_p was parallel to g while upright, and perpendicular to g when lying.

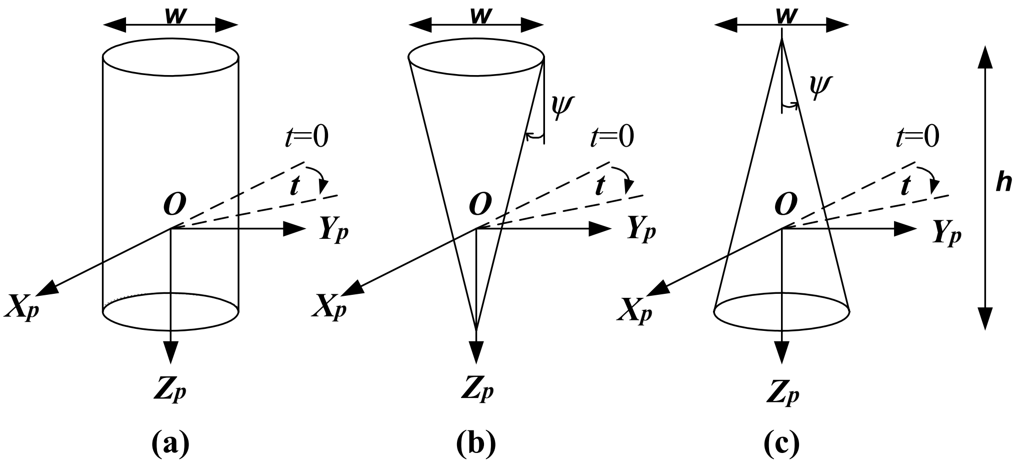


Figure 5.20: Types of three dimensional models that were tested: (a) no tapering, (b) uniform tapering, with apex towards the feet, and (c) uniform tapering, with apex towards the head.

Model Testing The measurements of the subjects' waists, and the data taken while the subjects were standing and lying supine with the TA in each of the six different placements were used to evaluate the models in three different ways. In the first part of the evaluation, the accuracies of the three horizontal cross-sections were compared. In the second part of the evaluation, the accuracies of the three dimensional models were assessed. In the third part of the evaluation the distribution of the data was studied to determine whether it would be better represented by a prismatic or a tapered model.

The accuracy of the horizontal cross-sections were evaluated by predicting the waist circumference of each subject by means of each of the cross-sectional models. The measured width and breadth of the subject's waist, l_x and l_y, were used to calculate the circumference of

(i) a rectangle, as $2(l_x + l_y)$;

(ii) an ellipse, (using the Ramanujan approximation) as

$$\pi.\left(3.\left(\frac{1}{2}l_x + \frac{1}{2}l_y\right) - \sqrt{\left(\frac{1}{2}l_x + \frac{3}{2}l_y\right)\left(\frac{3}{2}l_x + \frac{1}{2}l_y\right)}\right); \text{ and}$$

(iii) a circle, as $\pi.\frac{1}{2}.(l_x + l_y)$.

The calculated circumferences were compared with the measured circumference for each subject to give a preliminary validation of the waist cross-sectional models.

Each of the 20 s data recordings collected from the subjects was averaged to produce a single three-dimensional vector. This vector represented the TA output

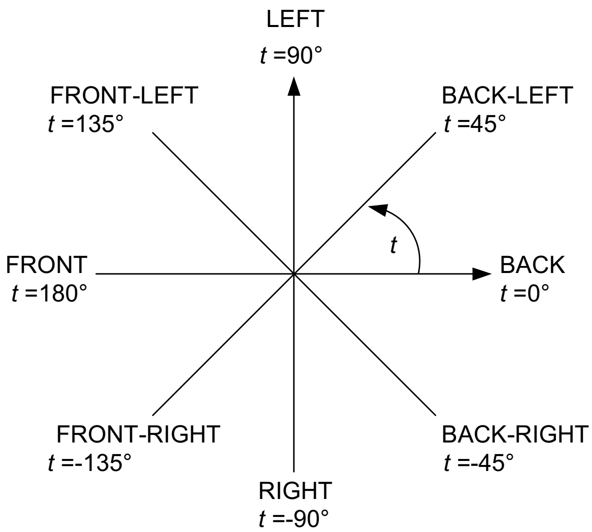


Figure 5.21: Figure showing the nominal values for the angle of placement, t_{nom}, for various positions on the waist.

for the subject for the given device placement and postural orientation. These vectors were used in the following analysis as the measured TA outputs.

Each of the models was evaluated by comparing the measured output of the TA with the output predicted by the model for each of the six placement locations. These six placement locations were nominally designated by $t = 0°$ at the back, $t = 90°$ at the left side, $t = 135°$ at the front-left, $t = 180°$ at the front, $t = 225°$ at the front-right and $t = 270°$ at the right side of the waist (refer to figure 5.21). These values are referred to as the nominal t values, or t_{nom}. The device was attached to the waist only in an approximate position as the angle t could not be measured directly. The problem thus became one of identifying the best model to represent the subject, and to identify the value of t that best represented each placement for each model.

A value for t was computed for every device placement for every subject. This was done by finding the value of t that minimised the difference between the measured output acceleration vector and the acceleration vector predicted by the model.

In order to do this, a three-dimensional least squares error term was defined as

$$e(t) = \sqrt{\left(g_{x(theor)}(t) - g_{x(meas)}\right)^2 + \left(g_{y(theor)}(t) - g_{y(meas)}\right)^2 + \left(g_{z(theor)} - g_{z(meas)}\right)^2} \tag{5.19}$$

where t is the angle of placement parameter, $g_{x(theor)}(t)$ is the (model-dependent) theoretical value for g_x, and similarly for $g_{y(theor)}$ and $g_{z(theor)}$. $g_{x(meas)}$ is the experimental value of g_x. The error term, $e(t)$, is measured in units of acceleration, $\mathrm{m.\,s^{-2}}$.

In the above equation g_z is independent of t and depends only on the vertical tilt angle, ϕ. g_x and g_y are described as functions of t. This was true for the elliptical and circular models, which produced a continuum of different output vectors depending on the value of t. It could also be applied to the rectangular models if t was restricted to one of the four values, 0°, 90°, 180° and 270°. In the rectangular model, placement at the front-left and front-right of the waist were reduced to a t-value of 180°, indistinguishable from the front placement. Consequently, optimisation of t was not undertaken when using the rectangular model.

When the models based on the ellipse and the circle were considered, the angle t that minimised $e(t)$ was calculated for each of the recorded measurements for each subject. These individual experimentally derived values for the angle of placement (t_{indiv}) were firstly compared to the nominal values (t_{nom}) as another check on the validity of the models. Then they were averaged over all of the subjects to produce a single mean experimental value for t for each device placement (t_{mean}). The different models were compared by considering the values of the error term, $e(t)$, that they produced. The models tested in this evaluation included the rectangular prism, regular and elliptical cylinders, the rectangular pyramid, and regular and elliptical cones.

The third part of the evaluation looked at the distribution of the data to determine whether a prismatic model was more appropriate than a tapered or a non-uniform model. If it is assumed that Z_p is vertically aligned when standing and horizontally aligned when lying then it may be noted that a prismatic model (and only a prismatic model) would result in the following behaviour for the tilt angle, ϕ:

1. When the subject is lying, the deviation about the nominal mean of 0 g can be either positive, if the head end of the device is elevated relative to the tail end, or negative if the tail end is elevated relative to the head end. Thus a distribution about zero is expected, with an experimental mean close to zero. (The tapered model would have a normal distribution about $g\cos(90° - \psi)$.)

2. When the subject is standing, the deviation about the nominal mean of $1g$ must result in a value less than one, and thus, if the data were normally distributed about one half a bell curve would be expected, with its peak at around one. (The tapered model would have a closer to normal distribution with peak at $g\cos\psi$.)

Subsequently the set of tilt angles for all subjects for all standing placements was compared to a normal distribution about zero, and the set of tilt angles for all lying placements was compared to half a bell curve.

The effects of subject height and waist circumference on the cone or pyramid and the effect of varying the amount of tapering were also considered.

Results

Waist measurements The mean measured waist circumference was 89.5 ± 8.0 cm (standard deviation). The rectangular model considerably overestimated the circumference of the subject at the waist (error = $23.8\% \pm 4.0\%$). The ellipse and the circle both gave much more accurate results (error = $-2.4\% \pm 3.1\%$ and $-2.8\% \pm 3.1\%$ respectively), but were more likely to underestimate the circumference. This is indicated by the negative sign in the error values.

Computation of the Angle of Placement, t Three different approximations to the angle of placement, t, were used. These were the nominal values, t_{nom}, the individually optimised experimental values, t_{indiv} and the group means of the individually optimised experimental values, t_{mean}. In the cylindrical models, t_{indiv} for each placement were similar across all of the subjects and were close to the t_{nom}. Figure 5.22 shows t_{mean} from the elliptical cylinder model plotted together with the t_{nom}. Each t_{indiv} was within one standard deviation of t_{nom} for the same postural orientation.

For each given nominal placement, the derived optimal angular position, t_{indiv}, had a standard deviation less than 13° (3.6% of the range), despite differences in body shapes and clothing worn.

The t_{nom}, t_{indiv} and t_{mean} values for each device placement were compared. Figure 5.23 shows the error term, $e(t)$, for the elliptical cylinder model when t_{nom}, t_{indiv}, and t_{mean} were used. Best results were obtained when the elliptical cylinder model was applied using t_{indiv}. This gave an overall mean placement error of $0.16 \pm 0.07\ g$ (standard deviation).

t_{indiv} provides the minimum possible value for $e(t)$. In the elliptical model, using t_{nom} rather than t_{indiv} doubled $e(t)$ at the asymmetric front-right placement, an increase from $e(t) = 0.11\ g$ to $e(t) = 0.22\ g$. For front-left placement an increase from $e(t) = 0.059\ g$ to $0.22\ g$ was found. t_{mean} resulted in error terms of $0.19\ g$, greater than the optimum but less than the nominal value. The difference between $e(t_{nom})$ and $e(t_{indiv})$ was less at the other symmetric placements that were tested, as is shown in figure 5.24.

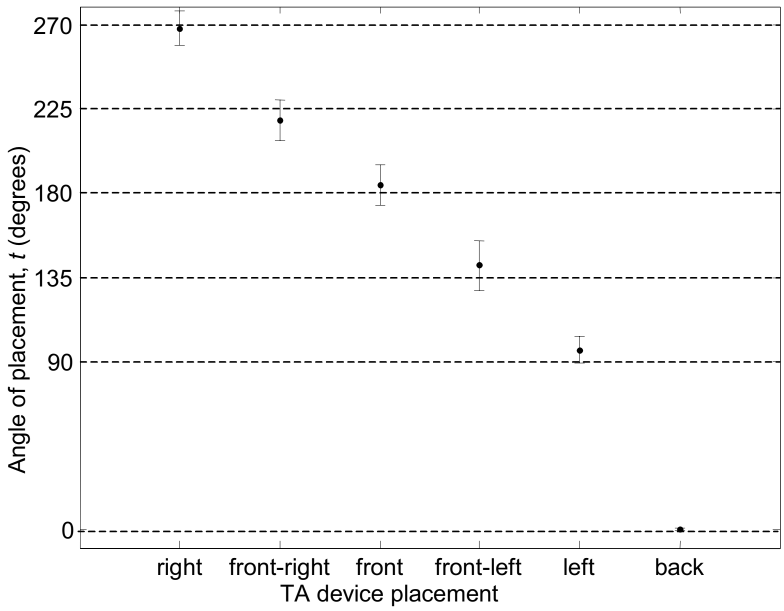


Figure 5.22: Mean experimental values (t_{mean}) for angle of placement parameter, t, using the elliptical cylinder model with subjects lying supine. The dotted lines indicate the nominal values for t (t_{nom}). Error bars represent 1 standard deviation.

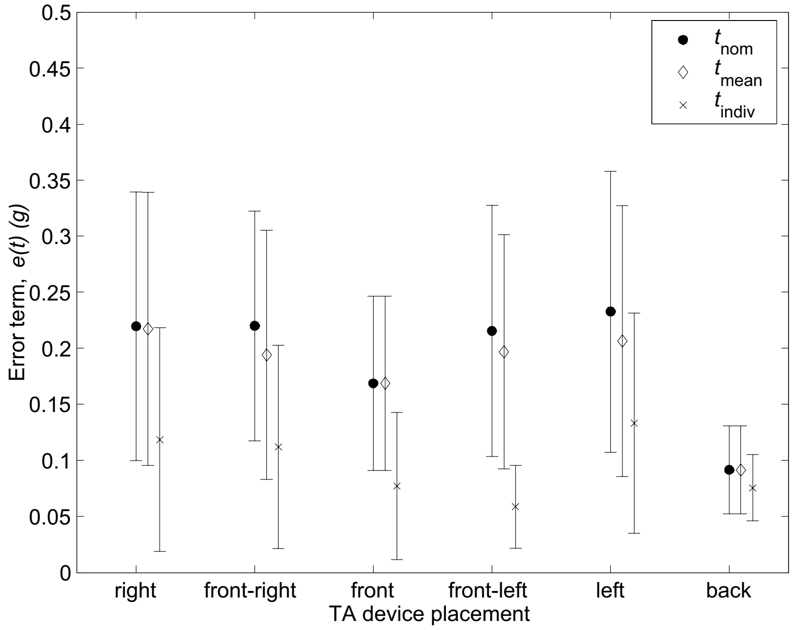


Figure 5.23: A comparison of mean $e(t)$ for the elliptical cylinder model with subjects lying supine using different approximations to t. Error bars represent 1 standard deviation.

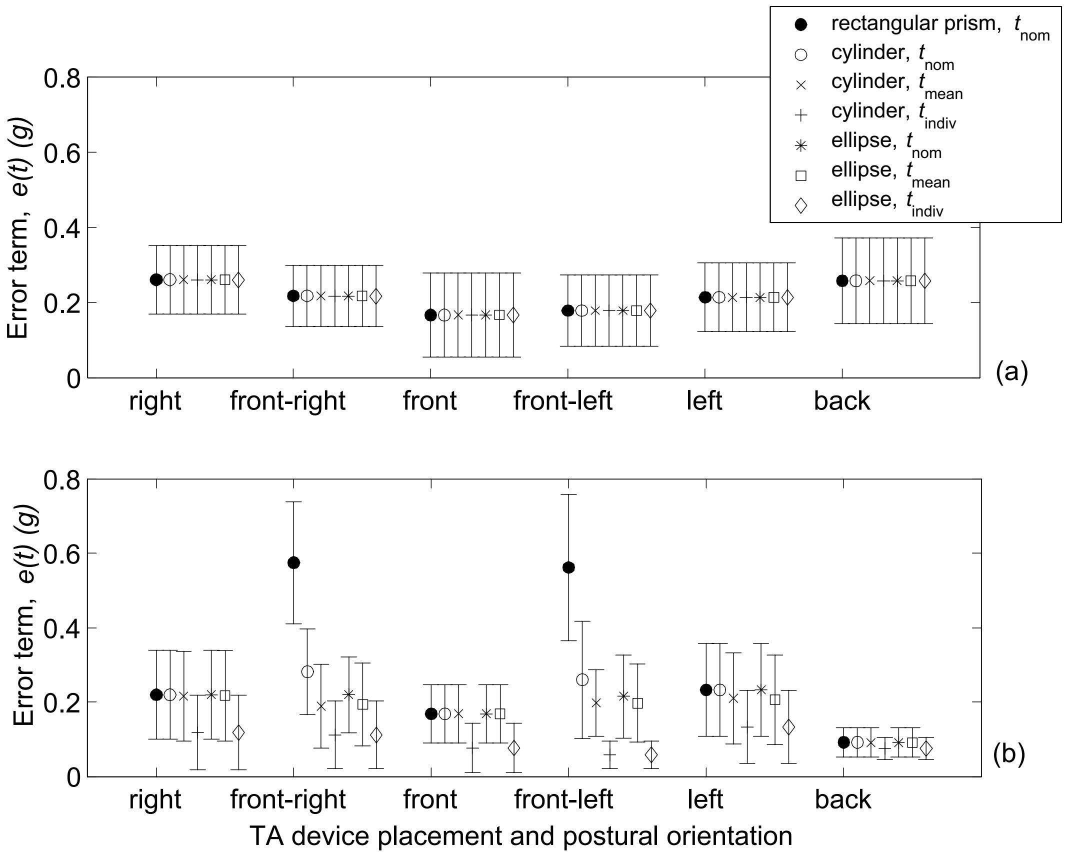


Figure 5.24: A comparison of the error term $e(t)$, from each of the three prismatic models, (i) the rectangular prism, (ii) the regular cylinder, and (iii) the elliptical cylinder at six placement locations, using (i) t_{nom}, (ii) t_{indiv}, and (iii) t_{mean} for subjects (a) standing and (b) lying supine. The t_{indiv} minimise the error term for each model. Error bars represent 1 standard deviation.

The results from the regular cylinder model were similar, although the disparity in error terms created using the different values for t were greater. Here, $e(t)$ was more than doubled at the front left and front right placements when t_{nom} was used rather than t_{indiv}.

Figure 5.24 shows the effect of using t_{nom}, t_{indiv} and t_{mean} to compute $e(t)$ for each of the three prismatic models. The experimentally derived angles of placement (t_{indiv} and t_{mean}) proved better parameters than the nominal angles of placement (t_{nom}). There was virtually no difference in accuracy between the results provided by the elliptical and circular models when t_{mean} were used, although the elliptical cylinder model performed better than the regular cylinder model when t_{nom} were used.

Vertical Axis Modelling In no case did a tapered model perform as well as the prismatic model with the same horizontal cross section. For some subjects, tapered models in which the apex was towards the head performed better than models tapered towards the feet, while in other subjects it was the other way around. No relationship was identified between the subject parameters (height, weight, l_x, l_y) and the optimal tapering angle. Changing the slope on the model had an effect on the accuracy of the system but as no relationship was found between the optimal slope and the subject parameters, this could not be generalised across subjects.

Figure 5.25 shows the mean z-axis value for subjects standing and lying supine in each of the six device placements. When lying supine, the mean measured value was within one standard deviation of the theoretical value. However, when standing, the mean z-value was less than the theoretical value for all subjects. Figure 5.26 shows histograms of the measured z-axis values for all subjects across all six device placements. When the subjects were lying supine, the distribution was almost Gaussian, following a bell curve with mean close to 0. When the subjects were standing upright, the data followed the lower half of a bell curve centred just below 1. The average value of g_z when subjects were standing was less than 1 because of the distribution of values around this point: 1 is the maximum value that can be achieved from the instrument, and deviation in any direction causes a reduction in this value. These distributions follow the patterns that would be expected if a uniform cross-sectional model was valid. This indicates that a prismatic model is an appropriate model choice.

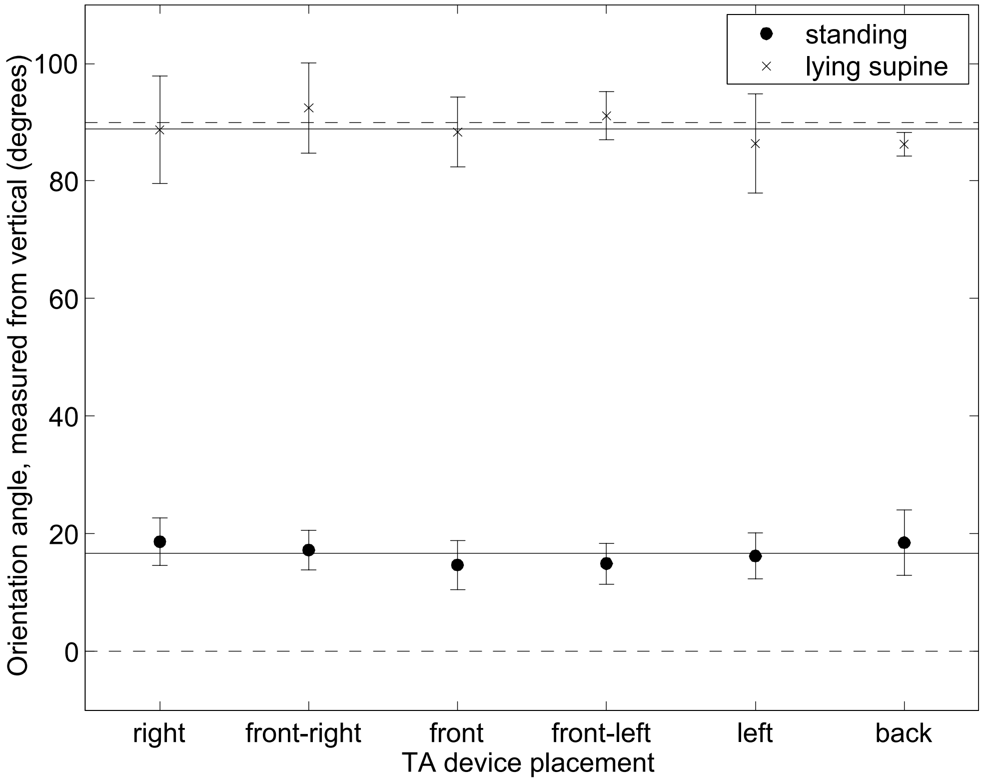


Figure 5.25: Mean experimental angles from vertical (ϕ) when subjects were standing and lying supine. The solid lines represent the overall mean experimental values. The dashed lines represent the theoretical values. Error bars represent 1 standard deviation.

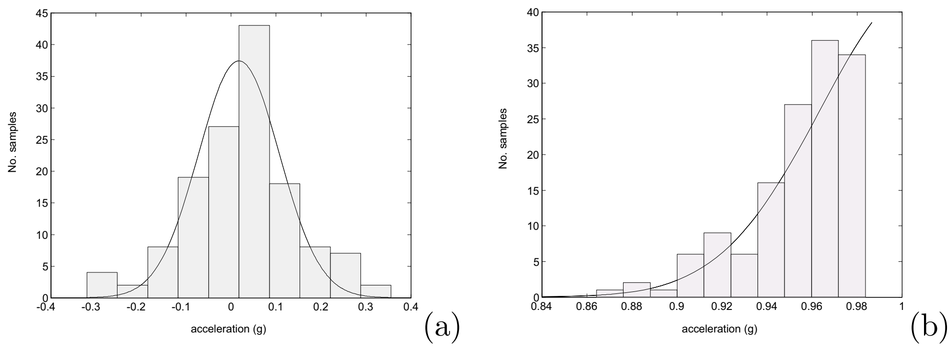


Figure 5.26: Histograms of measured g_z values when subjects are: (a) lying supine ($N = 138$); and (b) standing ($N = 138$).

Discussion

The elliptical cylinder provided the most accurate model, closely followed by the regular cylinder. The rectangular prism model performed well when the TA was located at the sacrum, but it did not generalise well to other, asymmetric placements around the waist (figure 5.24). When the TA was located above the right or left hip, the rectangular prism model performed poorly when compared to the cylindrical models.

The ellipse and circle would be expected to be better models of the cross-sectional waist than the rectangle and the ellipse would be expected to be superior to the circle. The circle captures the smooth, curved edges, whereas the rectangle has only flat, straight edges. The ellipse adds to the circle by incorporating the differences in length between the antero-posterior axis and the medio-lateral axis, while still providing reflective symmetry across the axes, thus maintaining the simplicity of the model. The two parameters, a and b, provide the ability to customise the ellipse to the particular subject. This hierarchy amongst the models is apparent in the accuracy with which the models predicted the waist circumference, although the ellipse offered only a small improvement over the circle.

This model hierarchy was retained when the prismatic models were evaluated. The circular model was appreciably more accurate than the rectangular model, but the elliptical model was only slightly better than the circular model. Given that the two cylindrical models had such similar accuracies, the regular cylinder has two advantages over the elliptical cylinder. The first that it is a simpler model since it has two less parameters. Secondly, the two ellipse parameters may be subject to variation over time (for example, if the subject changes weight, or wears different clothing), and so regular re-measurement may be necessary for the elliptical cylinder model. The circular model has the disadvantage that, since body shape is not taken into account, the experimentally derived parameters may be less able to be generalised to subjects with different body shapes to those of the tested subjects.

The small variation in the measured optimal angle of placement, t_{indiv}, across subjects (3.6% of the range), despite differences in body shape and clothing, suggests that results can be generalised across subjects, and that it is not necessary to know the exact placement of the device, but that knowing the nominal placement is sufficient.

Although the use of t_{indiv} gave the most accurate results, t_{mean} has a number of advantages over t_{indiv} that render them more practically useful. The t_{mean} are less sensitive to intra-subject variations than t_{indiv}. Also, the t_{mean} do not need to be experimentally calculated for each individual subject.

The ability to accurately predict the TA output for a given device placement and position suggests that a deterministic approach based on a model can be applied to classify the postural orientation of a subject when the device placement is known. It could also be used to identify the device placement when the postural orientation was known. Consequently, the cylindrical model was applied to the problem of classification of postural orientation, and this is discussed in the next chapter.

Conclusion

The present study was conducted to investigate the relationship between the signals produced by the triaxial accelerometer (TA), the postural orientation of the subject and the placement of the device on the subject at the waist. The geometry of the subject at the waist was modelled and the models were used to predict characteristics of the subject and the TA signal.

A cylindrical model accurately represented the shape of the subject. An elliptical cylinder model predicted the circumference of the subjects' waists with 97.6% accuracy. The mean angle of placement predicted by the model was within one standard deviation (3.6% of the range) from the nominal angle of placement of the device for each of the six placements. When the individual angles of placement predicted by the model (t_{indiv}) were applied, the overall error between the predicted and the experimental TA outputs was 0.16 ± 0.07 g (standard deviation).

Using a mean experimentally derived angle of placement, t_{mean}, and a regular cylinder slightly increased the error, but made the system more generalisable by removing patient-specific parameters.

The results obtained in this study indicate that a simple model provides a robust method for relating TA placement and postural orientation to the signals obtained from a TA.

5.4.4 Restrictions on Device Placement

As discussed earlier, the TA device needed to be attached at the waist in order to be near the centre of mass of the subject. Many researchers using accelerometers placed a device at the sacrum [20, 31, 56, 70, 99, 199]. There are three main reasons for this choice. The first is that at the sacrum there is bilateral symmetry. The second is that the low back has little soft tissue, and the accelerometer can be firmly attached against the bony matter where there will be less artefact due to soft tissue movement. The third reason is that attachment to the low back was found to cause minimal discomfort to the subjects and did not influence the performance of daily activities [31].

However, reaching to place a device on the back is difficult for many potential users of the system, especially those with a disability such as arthritis. Moreover, wearing this particular TA device at the back leads to some discomfort when sitting and lying. Most importantly, it makes the push-button on the device difficult to reach. For these reasons, positioning the device at other locations on the waist was investigated.

Accelerometers have been attached to the front of the waist [157] and to the sternum [72, 76] as part of instrumentation systems for activity classification. One investigator placed accelerometers on the left and right hips to assess physical activity levels [74].

The TA device used in this study was presented to thirty normal healthy subjects. Subject were asked to attach the device at their waists, either to their belt or to the top of their trousers or skirt. Subjects were asked to walk around, sit down and lie down and then to decide which location they found most comfortable. Most subjects chose to position the device above the anterior superior iliac spine as this was the most comfortable and easiest point of attachment, although two subjects preferred to attach the device at the right hand side of the body.

Positioning the device above the anterior superior iliac spine has two drawbacks in terms of the signal obtained when compared to attachment at the sacrum. Firstly, there is more soft tissue at the front of the body than at the low back and so the signals are more likely to be affected by artefact, although this effect would be expected to be less than if the device was attached in the middle of the front of the waist. Secondly, the device is not aligned with bilateral symmetry and this leads to some distortion of the output signal, particularly during walking, thus making it more difficult to analyse.

However, it was hypothesized, and is demonstrated in the current work, that important characteristics of the body acceleration signal can still be determined using a placement above the anterior superior iliac spine. It was determined that the advantages of patient comfort and usability outweighed the disadvantages of using an asymmetric placement. The following work focussed on understanding the signals obtained from a TA that was placed above the right anterior superior iliac spine. Two studies were conducted to investigate the effect of device placement on accelerometer signal output during activity. The first study investigated the effect of placement on the sit-stand-sit movement. The second study investigated the effect on the signal during normal walking.

5.4.5 A Study of the Effect of Device Placement on Signals Obtained During Sit-to-Stand and Stand-to-Sit Transfers

Introduction

The sit-to-stand transfer has been described as consisting of three main components: a lean forward, a vertical rise, and a straightening up (refer to section 3.5). The stand-to-sit transition has been described similarly, with the components occurring in the opposite order. Bilateral symmetry is normally assumed in these transitions [151].

This study investigated the effect of device placement on the signals derived from a TA during sit-to-stand and stand-to-sit transitions. The aim of the study was to attempt to quantify the relationship between the placement location and the output signals during sit-to-stand and stand-to-sit transitions, using the cylindrical model that was successfully applied to model the relationship between postural orientation and placement location (section 5.4.3).

Experimental Procedure

Two TA units were required for the study in order to allow the accelerations at two locations on the waist to be measured simultaneously. As the TA units all transmitted at the same frequency (433.92 MHz) they could not be used in a wireless mode, and so two TA units were hardwired to two receiver boards.

The TA units and their receiver boards were attached to an elastic belt that was worn around the waist. The two TAs were positioned so that one was above the sacrum at angle of placement $t_{nom} = 0$ (the back TA), and the other was placed at different locations around the waist during the study (the front TA). The back TA was attached so that the x-axis of the TA corresponded to the antero-posterior axis of the subject, the y-axis to the medio-lateral axis, and the z-axis to the vertical axis. The front TA was attached so that its z-axis also corresponded to the vertical axis of the subject, but the alignment of the other two axes depended on the placement of the unit. The receiver boards were connected to the power supply and to the personal computer by long, light cables that did not interfere with the subject's movement. Data from the TA units were recorded by a personal computer. Each data sample from each TA was time-stamped as it was received by the computer.

Eight normal, healthy subjects aged between 25 and 40 years were tested. Each subject was asked to stand up from a chair and sit down into the same chair, twenty-five times in total. Five repetitions of each transition were performed using the same chair with the front TA attached in each of five positions:

1. at the right side of the waist, $t_{nom} = 270°$,
2. above the right superior anterior iliac spine, $t_{nom} = 213°$,
3. at the front of the waist, $t_{nom} = 180°$,
4. above the left superior anterior iliac spine, $t_{nom} = 147°$, and
5. at the left side of the waist, $t_{nom} = 90°$.

This resulted in a total data set of 200 sit-to-stand transitions, and 200 stand-to-sit transitions.

The angles of placement were determined in the study of the effect of device placement on signals obtained during rest (section 5.4.3) when the surface of the pelvis at the point of TA attachment was modelled as a regular cylinder. The same model was used in this study due to its good performance in modelling the relationship between TA signal and postural orientation.

There was a delay of 10 s between the completion of one transition and the commencement of the next to ensure that there was no overlap between adjacent activities. The procedure took around thirty minutes to complete.

Data Analysis

The data from each of the TA units was median filtered ($n = 3$) and resampled at 40 Hz such that the samples from each TA occurred at the same time. (Since data from the two TA units were sampled asynchronously, the data from each unit had the same sampling rate, but the samples did not occur at the same time.) The resampling was done using the Matlab function "resample[1]". This function applies a linear phase, finite impulse response (FIR) filter with a Kaiser window for anti-aliasing, and then uses a polyphase filter for resampling [161].

The Fourier transforms of the signals from both of the TA units were inspected to confirm that almost all of the signal energy was contained below 3 Hz. As this was the case, the signals from both of the TA units were low pass filtered at 4 Hz to remove high frequency components from the signals and leave only the main frequency components of the signals.

The vector signals from the front TA were rotated about the z-axis with an angle of rotation equal to the negative of the angle of placement associated with the TA

[1] Signal Processing Toolbox

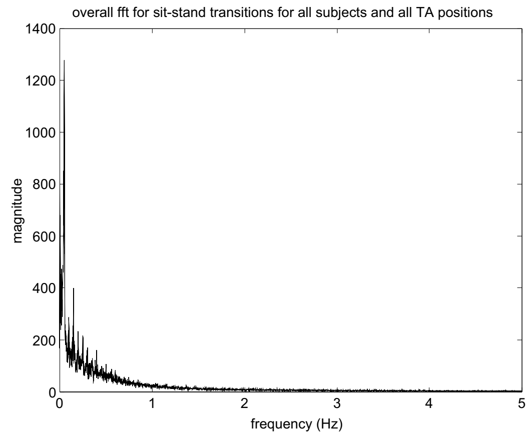


Figure 5.27: Mean Fourier transform taken across all 400 sit-to-stand and stand-to-sit transitions.

placement location. For example, when the front TA was placed at the right side of the waist, the front TA signals were rotated about the z-axis through $-270°$. This transformation was equivalent to aligning the front TA so that its axes were parallel to those of the back TA, and this allowed the signals from the two TAs to be directly compared. The signals from the two TAs were then compared by visual inspection of the signals in the time and frequency domains, calculation of the error between the two signals (measured as the average distance between each corresponding pair of points in the two signals) and calculation of the cross correlation between the two signals.

Results

Figure 5.27 shows the mean Fourier transform of the signals, before filtering, for all subjects. It can be seen that there is no significant frequency component above 4 Hz, which was the frequency at which the signal was low pass filtered.

There was no significant difference between the results obtained for the sit-to-stand transition, and the stand-to-sit transition in any of the analysis. The results have been presented here for both transitions combined.

Typical signals from the front (rotated) and the back TAs are shown in figure 5.28 when the front TA was attached at the front-right.

Figure 5.29 shows the mean cross correlation between the back TA and the front TA for each of the positions at which the front TA was placed. The x-axes were highly correlated (mean $r = 0.870 \pm 0.225$ standard deviation). There was a moderate correlation on the z-axis (0.460 ± 0.333) but only a low correlation on the

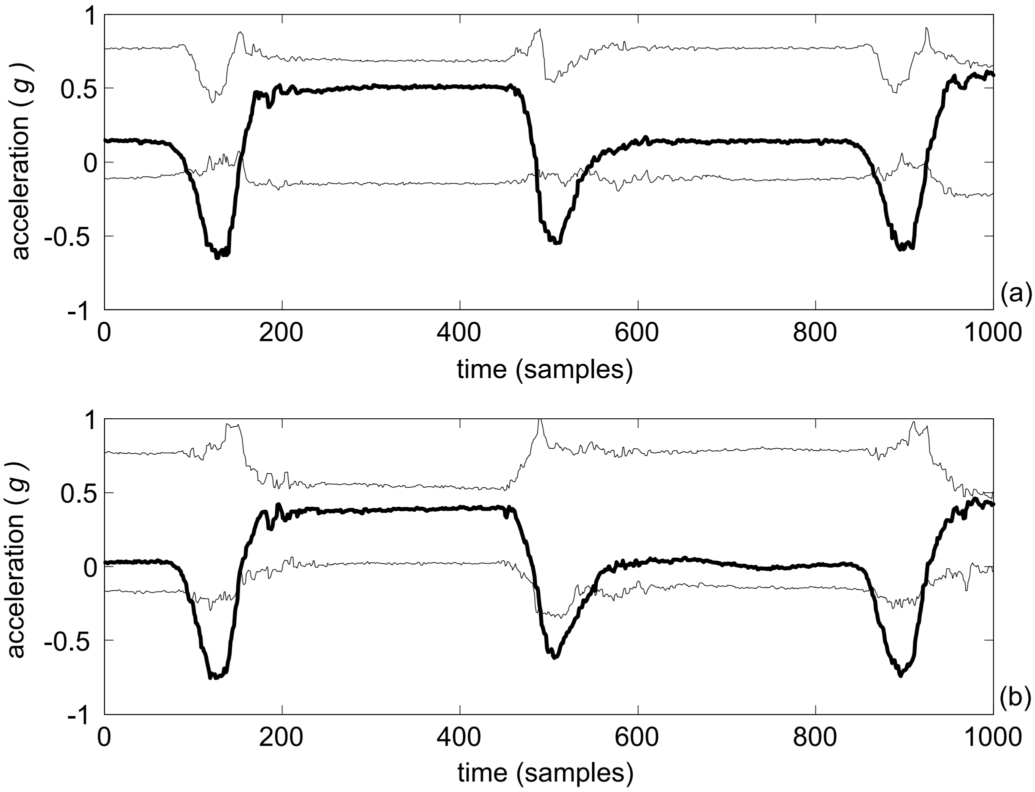


Figure 5.28: Typical sit-to-stand and stand-to-sit transition signals measured by 2 TAs from one subject. (a) signals from back TA. (b) signals from front-right TA, rotated $-213°$ about the z-axis. In both figures, the top signal is the z-axis signal, the bold signal is the x-axis signal and the lower signal is the y-axis signal.

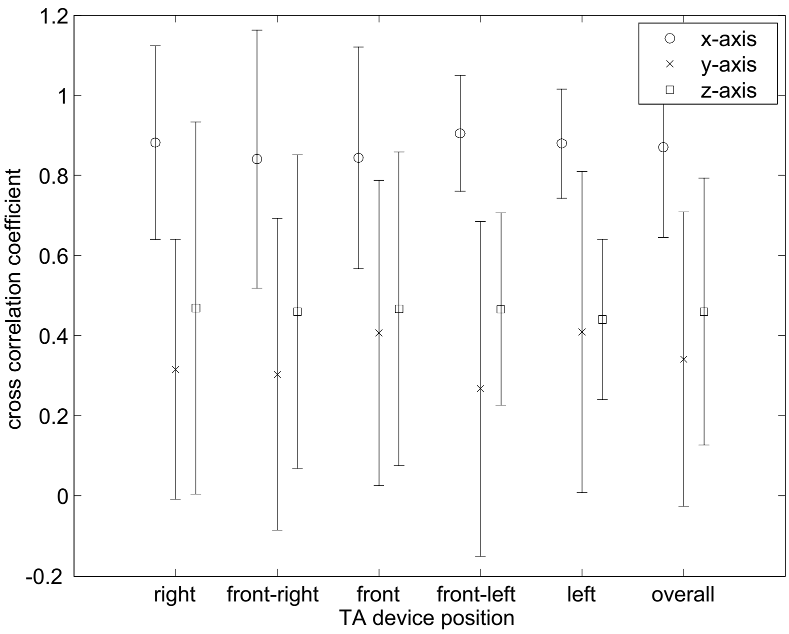


Figure 5.29: Mean cross correlation coefficients between the sit/stand transition signals across 400 transitions from 8 subjects. The front TA was placed at the locations shown. The signals from the front TA were rotated about the z-axis and correlations between the rotated signals and the signals from the back TA were measured. Error bars represent 1 standard deviation.

y-axis (0.341 ± 0.368).

Figure 5.30 shows the errors between the back TA signal and the rotated front TA signal as a function of the signal range for that subject and that placement. In each case, the greater of the ranges from the back and the front TAs was used as the signal range. The mean error was $8.1 \pm 5.4\%$ (x-axis: $8.2 \pm 6.3\%$, y-axis: $7.1 \pm 4.8\%$, z-axis: $9.1 \pm 5.2\%$).

Discussion

The cylindrical model proved very effective at relating the signals from the TAs during sit-to-stand and stand-to-sit transitions. The signals from the three axes followed the same general shape in the two TA outputs during the transitions. However, the starting and ending values and the peak acceleration magnitudes differed between the front and back placements. This was particularly true on the z-axis.

These differences in the z-axis can be attributed to different starting tilt angles in the accelerometers. The nonlinear relationship between tilt angle and z-axis

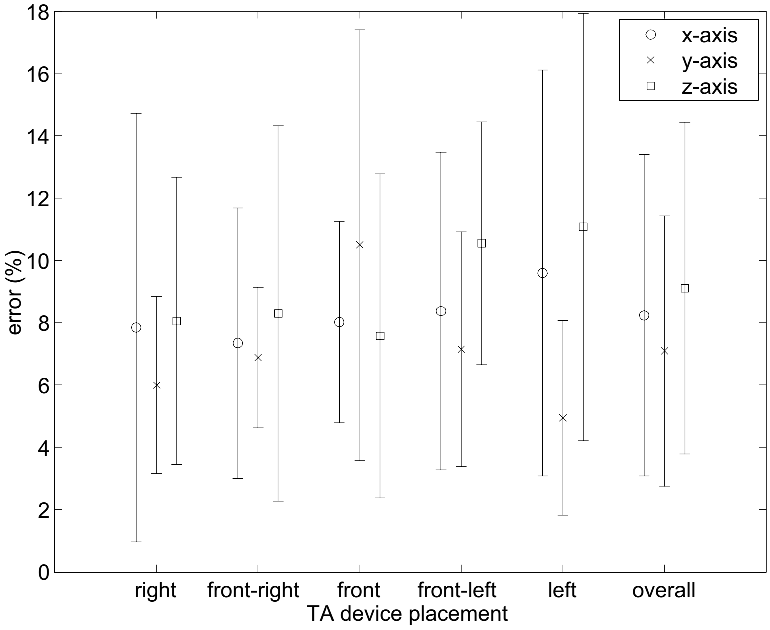


Figure 5.30: Mean errors between the back TA signal and the rotated front TA signal as a function of TA placement and as a percentage of the signal range for signals from 400 transitions across 8 subjects. Error bars represent 1 standard deviation.

output means that a small difference in angle can be magnified to result in larger differences between z-axis values. Subjects were encouraged to sit comfortably, as they would normally sit. Most of the subjects sat back in the chair, and in several cases, the back TA was touching the back of the chair, which may have had a slight effect on the orientation of the back TA. This could have been overcome by using a stool rather than a lounge chair, but housebound subjects are more likely to sit on a lounge chair than on a stool. Hence the lounge chair was used in order to capture data that would better reflect transitional movements of a subject in the home.

There was also some artefact introduced into the signals by soft tissue movement at the front placements and movement of clothing during the transitions. The acceleration magnitudes on the y-axis were small due to the bilateral symmetry of the transitions which meant that there was little movement in the medio-lateral direction. This led to the relative proportion of artefact in the signal becoming larger than on the other axis signals, and resulted in lower cross correlation coefficients on this axis.

Every transition could be seen to contain the three basic components of the movement but, within this, there were many individual variations. The general shape of the signals was similar between the two TAs on all three axes. This can be seen visually in the signals (figure 5.28). It can also be seen when the errors between the front and back TA signals are considered (figure 5.30). The amount of error is comparable on all three axes, and is around 8% of the range of the signal. In absolute terms, these errors are small. The mean errors of 8.2%, 7.1% and 9.1% correspond to 0.104 g, 0.068 g and 0.078 g on the x-, y- and z-axes, respectively. After differences of starting tilt angle and artefact are taken into account, this represents a good agreement between the signals from the back TA and the transformed signals from the front TA.

The ability to relate sit-stand-sit movement signals from TAs at different parts of the waist is important for use in an unsupervised monitoring system in which the device placement may vary. This allows parameters to be extracted and directly compared without needing the TA device to be identically positioned each time. It also demonstrates that parameters measured on different subjects can be directly compared even though the device placement will not be identical between the subjects.

Conclusion

This study investigated the relationship between the signals from a TA attached at the back of the waist and a TA attached at the front of the waist during sit-to-stand and stand-to-sit transitions. A data set of 400 transitions taken from 8 normal, healthy subjects was used. The signals were compared by means of a simple model in which the subject was represented by a regular cylinder.

The results of the study demonstrated that this model can be used to relate the signal obtained from the back TA to the signals obtained at other TA placements on the waist with a high degree of accuracy. Using this model, the back TA signal was able to be predicted by the other TA signal with a mean error of $8.1 \pm 5.4\%$ of the signal range, corresponding to an absolute mean error of $83 \pm 54\,\mathrm{m}g$.

5.4.6 A Study of the Effect of Device Placement on the TA Signal Obtained During Walking

Introduction

Walking is a complex, nonlinear movement with constantly changing accelerations. The details of the movement are individualistic and are also dependent on walking speed.

The signals derived from a sacrum-mounted accelerometer during walking have been studied by several researchers. The components of the signal have been related to the components of the gait cycle [70], parameters of gait have been extracted from the signal [20, 56, 70], and information regarding the normality of the gait pattern has been obtained [73, 199]. This work was discussed in section 3.6.6.

These results were derived from systems in which the TA was placed at the sacrum. The purpose of this study was to understand the relationship between the signals from a TA placed at the back of the waist and a TA placed at the front-right of the waist during walking. The intent was not to characterise gait—gait is already well characterised and understood—but rather, to understand the effect of placement location on the TA signals and hence to identify features of gait that can be extracted from a single TA attached at the front right of the waist.

There were three parts to the study, each with its own aim:

1. to investigate the extent to which the cylindrical model of the pelvis can relate the signals at the back and front-right of the waist during walking;

2. to adapt a simple six degrees-of-freedom model of pelvic displacement during walking (refer to section 3.6.4) to predict accelerations and then to evaluate the performance of this model in representing the accelerations at the back ($t_{nom} = 0°$) and front-right ($t_{nom} = 213°$) of the waist during walking; and

3. to investigate the extent to which the information on gait that can be derived from a sacrum mounted accelerometer (as addressed in the literature) can be obtained from a TA attached at the front-right of the waist ($t_{nom} = 213°$).

Experimental Procedure

Two TA units were required for the study in order to allow the accelerations at two locations on the waist to be measured simultaneously. As the TA units all transmitted at the same frequency (433.92 MHz) they could not be used in a wireless mode, and so two TA units were hardwired to two receiver boards.

The TA units and their receiver boards were attached to an elastic belt that was worn around the waist. The belt was fitted snugly to the waist of the subject. The two TAs were positioned so that one was at $t_{nom} = 213°$ above the right anterior superior iliac spine (front TA) and the other was at $t_{nom} = 0°$ (back TA). The back TA was attached so that the x-axis of the TA was aligned with the antero-posterior axis of the subject, the y-axis with the medio-lateral axis, and the z-axis with the vertical axis. The front TA was attached so that its z-axis was also aligned with the vertical axis. The receiver boards were connected to the power supply and to the personal computer by long, light cables that did not interfere with the subject's movement. Data from the TA units were recorded by two computers. The clocks of the two computers were synchronised before each trial and the data samples recorded from each TA were time-stamped to the nearest millisecond.

A treadmill with controllable speed and incline was used for the study. The incline was set to zero for all trials.

Twelve normal, healthy subjects, five female and seven male, with no gait impediments, aged between 25 and 60 years, agreed to participate in the study. The experimental procedure, outlined below, was explained to the subject. The belt with the TA units was attached to the subject who then practised walking on the treadmill at various speeds. It took two to three minutes for a subject to feel comfortable walking on the treadmill.

The subject was told to jump, then to bow, then to jump again, and to bow again. These signals were used as a reference by which to check the synchronisation of the signal traces from the two instruments. The treadmill was started and the subject walked at each of 2, 3, 4, 5, 6 and 7 $\mathrm{km.\,h^{-1}}$, for 5 minutes at each speed. If the subject was unable to complete 5 minutes at a particular speed then this was excluded from the study. The order of the speeds was varied for different subjects. At the completion of the test, the treadmill was stopped. The subject was asked to jump and to bow twice more to provide a synchronisation reference at the end of the test.

The complete test took about 45 minutes to complete for each subject.

Data Analysis

The signals from each of the TAs were aligned and resampled at 20 Hz so that the samples from the two TAs coincided in time. The signals were down-sampled because 95% of the signal power during walking is contained below 10 Hz [21] and the aim in this study was to compare the main signal components of the gait, not the high frequency perturbations.

The first 90 s and last 30 s of the signal at each new walking speed were discarded so as to avoid any irregularities that may have occurred in the gait while the subject was adapting to the new speed or growing tired at the end of the five minute segment. This resulted in a three minute sample being extracted for analysis at each speed.

Part 1. Application of the Cylindrical Model The cross-correlation between the front-right and back signals was computed for each of the three axes. The cylindrical model developed in section 5.4.3 was applied to the data. The signals from the front-right TA were rotated about the vertical axis to represent placement at the back. The cross-correlations between these rotated signals and the signals from the back TA were then computed.

Part 2. Adaptation and Application of the Displacement Model The second aim of the study involved application of the gait displacement models that were described in section 3.6. Prior research has found that pelvic displacement during walking can be accurately represented by a model with six decoupled degrees of freedom, all of which are represented by sinusoids [53, 81, 108]. The aim was to investigate the performance of this model in modelling pelvic acceleration. This was done by deriving predictors of the acceleration signals using the displacement model and then comparing the predicted signals to the measured acceleration signals.

A model that related placement location to TA signal output during walking was developed, and its performance was evaluated. The model was developed with six fully decoupled degrees of freedom. Each dimension was modelled by a sinusoid. The model starting equations were based on the equations of Gard *et al.* [81] and are listed below.

$$
\begin{aligned}
x &= x_m \sin(\omega t) && \text{(lateral translation)} \\
y &= -y_m t && \text{(forward translation)} \\
z &= -z_m \sin(2\omega t - \tfrac{\pi}{2}) = z_m \cos(2\omega t) && \text{(vertical translation)} \\
\alpha &= \alpha_m \sin(2\omega t - \tfrac{\pi}{2}) = -\alpha_m \cos(2\omega t) && \text{(x-axis rotation)} \\
\beta &= \beta_m \sin(\omega t) && \text{(y-axis rotation)} \\
\gamma &= \gamma_m \sin(\omega t - \tfrac{\pi}{2}) = -\gamma_m \cos(\omega t) && \text{(z-axis rotation)}
\end{aligned}
$$

where t is the time in seconds, ω is the angular frequency in rad.s^{-1}, and $x_m = 2.5$ cm, $y_m = 140$ cm, $z_m = 2.5$ cm, $\alpha_m = 2.5°$, $\beta_m = 2.5°$, $\gamma_m = 5°$ were used as starting values. The values for these parameters were obtained from the literature (refer to section 3.6). The frequencies of the sinusoids (i.e. the ω) were determined by the step rate. The derivation of the acceleration model from these equations is given in Appendix A.

During analysis, the model parameters were varied from zero up to twice their starting values. Parameters were chosen to minimise the differences between (i) the predicted and measured signal frequencies, (ii) the predicted and measured phase relationships between the signals from the three axes, and (iii) the measured and predicted acceleration magnitudes, for each of the two measured TA placements. The predicted accelerations were compared to the measured accelerations.

Part 3. Extraction of Gait Information from the Front-Right TA Signal The aim of the third part of the study was to identify the components of the gait cycle in the signals from the TA placed above the anterior superior iliac spine, based on the results for the sacrum-mounted TA. The data obtained at the sacrum were visually inspected. The signals were compared to published results in order to interpret the signal in terms of the components of the gait cycle. The signal from the front-right TA was compared to the signal from the back TA in terms of signal characteristics including phase, timing of peaks and troughs in the signal and the presence of local turning points and inflexions. Fast Fourier transforms were taken of all of the signals to test whether the signals from the three different TA axes had the same periodicity (as would be expected).

Results

One subject was unable to complete the walk at $6\,\mathrm{km.\,h^{-1}}$ and did not attempt the walk at $7\,\mathrm{km.\,h^{-1}}$. All other subjects successfully completed the procedure at every speed.

Part 1. Application of the Cylindrical Model Before applying the model, the cross correlation between the TA signals from the two locations were computed. The mean cross correlation coefficient between the two vertical signals was moderate (between 0.6 and 0.8), and increased with increasing walking speed. The mean cross correlation coefficient between the two forward acceleration components was negative, as would be expected since these axes were pointing in different directions. There was no correlation between the y-axis acceleration components.

When the signals from the front-right TA were rotated about the vertical axis to represent a reorientation of the front-right TA a new set of cross correlation coefficients was obtained. The mean cross correlations across all subjects, as a function of

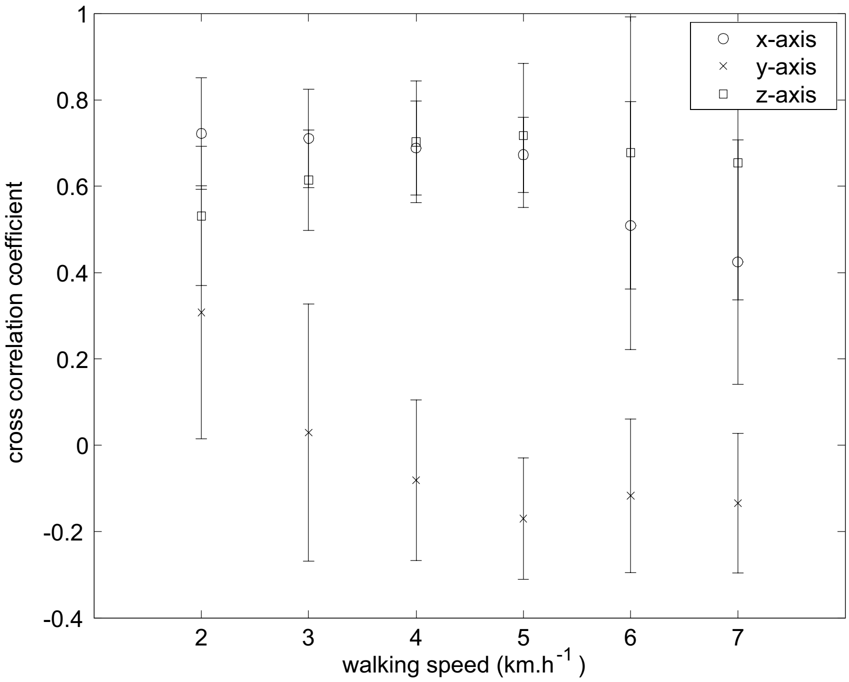


Figure 5.31: Mean cross correlation coefficients between the signals from the two TA units at each walking speed. Data were composed of three 60 s samples from each of 12 subjects. Error bars represent 1 standard deviation.

	Walking speed	2km/h	3km/h	4km/h	5km/h	6km/h	7km/h
x-axis	raw x-corr	-0.669	-0.644	-0.678	-0.589	-0.529	-0.445
	rotated x-corr	0.754	0.747	0.710	0.673	0.619	0.516
y-axis	raw x-corr	-0.029	0.152	0.202	0.209	0.195	0.163
	rotated x-corr	0.251	-0.025	-0.123	-0.176	-0.168	-0.1739
z-axis	raw x-corr	0.535	0.599	0.679	0.722	0.787	0.729
	rotated x-corr	0.535	0.599	0.679	0.722	0.787	0.729

Table 5.4: Mean cross correlation coefficients between the acceleration component signals (x-axis, y-axis and z-axis) across all subjects from the TA at the back and the TA at the front-right of the waist. One subject did not complete the $6\,\mathrm{km.\,h^{-1}}$ nor the $7\,\mathrm{km.\,h^{-1}}$ walk so these cross correlations were computed for the remaining 11 subjects. All other cross correlations were calculated for all 12 subjects. The raw cross correlation coefficients were obtained by directly measuring the cross correlation between the two signals. The rotated cross correlation coefficients were obtained by rotating the signals from the front-right TA about the z-axis and measuring the correlation between these signals and the acceleration signals from the TA attached at the back.

walking speed, are shown in figure 5.31. The cross correlation coefficients from before and after the rotation are compared in table 5.4. This transformation improved the cross correlation on the x-axis, but had little effect on the correlation between the y-axis signals. The transformation had no effect on the z-axis correlation since the rotation left the z-axis data unchanged.

Part 2. Application of the Displacement Model Typical acceleration signals produced by the model are shown in figure 5.32 for TA placement at the back and at the front-right of the waist. The acceleration signals from the model did not accurately reflect the measured acceleration signals. This can be seen by comparing the illustrated model output with the illustrated gait accelerations shown in figure 5.37. The signals produced by the model were smooth, curved signals, while the actual acceleration signals were much spikier, and contained many small peaks and troughs between the global minima and maxima.

However, although the model could not capture the detail of the signals, it could correctly represent the phase between the component accelerations. Also, when the displacement parameters from the literature were applied to the model, the peak accelerations given by the model on each of the axes were close to the mean peak accelerations measured during walking at $4 - 5\,\mathrm{km.\,h^{-1}}$. The displacement parameters vary with changes in walking rate, and when these were applied to the model, the model peak accelerations changed accordingly and continued to

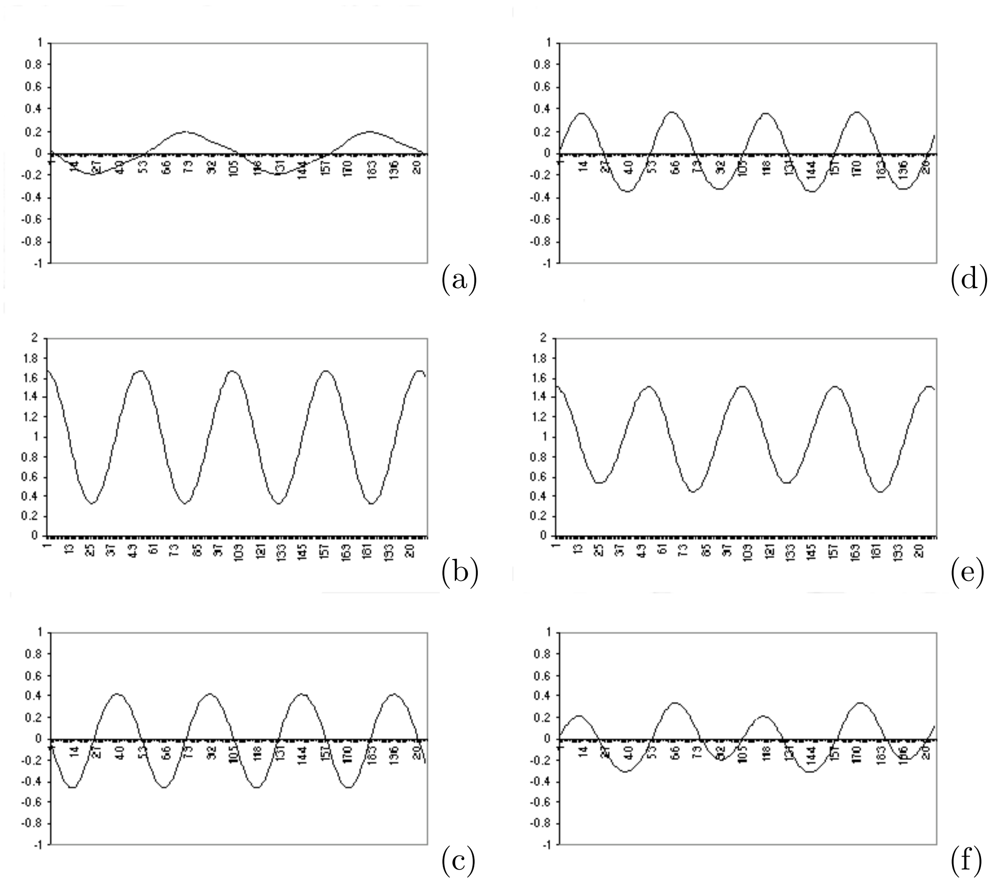


Figure 5.32: Prediction of acceleration signals from the sinusoidal model of pelvic movement: acceleration (g) versus time (arbitrary units). Left side: TA attached at the back. (a) y-, (b) z-, and (c) x-axis accelerations. Right side: TA attached front right. (d) y-, (e) z-, and (f) x-axis accelerations.

reflect the mean peak accelerations in the measured signals at the relevant speeds. However, to achieve this, the model parameters needed to be adjusted for each subject at each walking speed.

As the actual walking signals were not well represented by the model, this approach was not used to relate the TA signals from the two placements.

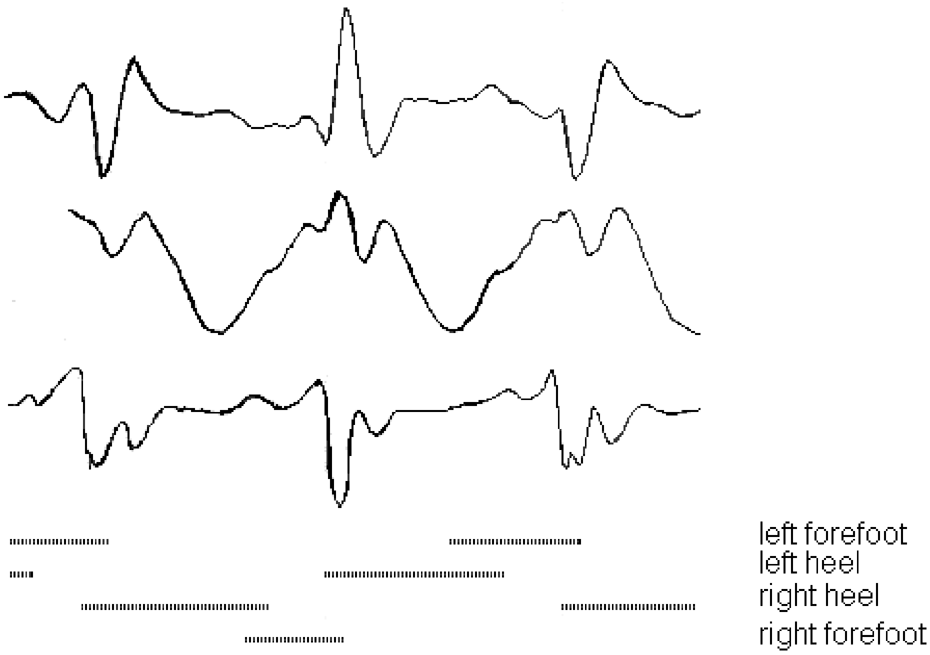
Part 3. Extraction of Gait Information from the Front-Right TA Signal
The TA device attached at the back produced accelerometer signals (figure 5.33b) that were visually comparable to those obtained by Evans *et al* [70] (figure 5.33a). The timing within the gait cycle is indicated in figure 5.33a by the microswitch signal. This shows when the heels and forefeet of the subject in Evans' study were in contact with the ground, relative to the acceleration signals.

As noted by Evans, the inflections in the vertical signal can be used to identify the beginning of the step (heelstrike) and the end of the previous step (push-off), thus giving an identifiable means of measuring the double support and single support times. The heelstrike corresponds to local minima or maxima before the global peak on the lateral acceleration signal, and to the maxima on the forward acceleration signal. The forefoot strike corresponded approximately to the global minima in the vertical acceleration signal. The forefoot was lifted at the same time as the peak accelerations occurred in the lateral and the forward acceleration signals. There is one global maxima or minima in each signal for each step taken and so the step period could also be identified from the signal.

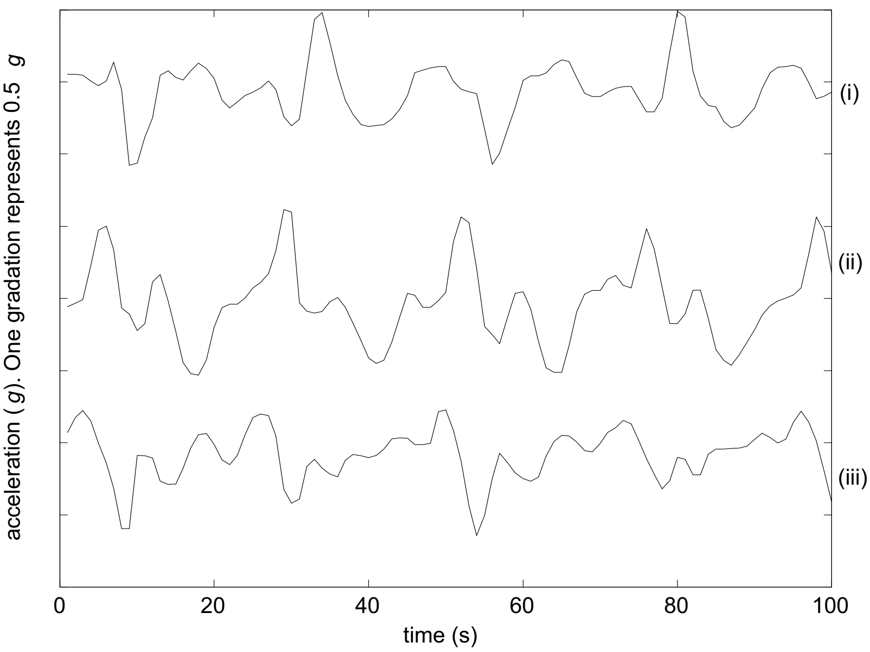
The gait pattern was dependent on the walking speed. The differences in gait pattern as a function of walking speed are illustrated in figure 5.34. The timing of the gait components and the step cadence could be identified from the sacrum mounted TA signal for each subject at each speed.

When Fourier transforms were taken of the signals from the two TAs it was found that the front-right TA and back TA signals contained the same frequency components, although the magnitudes of the frequency peaks differed. The Fourier transforms that were obtained are illustrated in figure 5.35, which shows the Fourier transforms for the normalised walking signals obtained from one subject walking at $5\,\mathrm{km.\,h^{-1}}$. All of the signals contained the same fundamental frequency, which represented the step rate. The signals from the front-right TA had more harmonic component present than the signals from the back TA.

The z-axis accelerations had the most similar frequency spectra, while those of the y-axis accelerations were the least similar. This is reflected in the mean cross-correlation coefficients between the Fourier transforms of each of the signals at each



(a)



(b)

Figure 5.33: Acceleration signals from two normal healthy subjects walking at a normal speed. Figure (a) shows data obtained by Evans *et al.* Top acceleration signal: lateral acceleration; middle: vertical acceleration; and bottom: forward acceleration. The fourth signal was obtained from a microswitch and shows when the subject's heels and forefeet were in contact with the ground. Reproduced from Evans *et al.* [70]. Figure (b) shows walking data obtained in the current study when the TA was attached at the back of the waist. (i) y-axis; (ii) z-axis; and (iii) x-axis signals. The signals have been vertically shifted relative to each other so that they are presented in the same order as those of part (a).

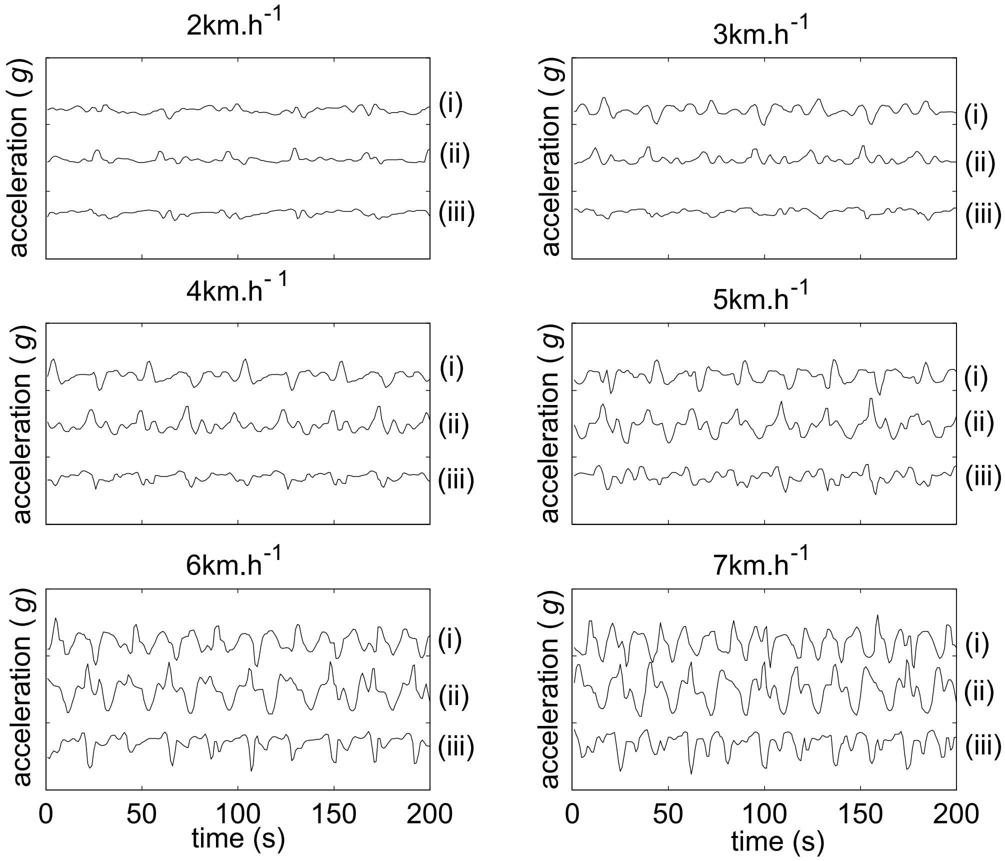


Figure 5.34: Signals obtained from a sacrum mounted TA during treadmill walking at different speeds by a normal, healthy subject. All graphs show accelerations from the three axes plotted against time. (i) y-axis; (ii) z-axis; and (iii) x-axis. All graphs are plotted on the same scale.

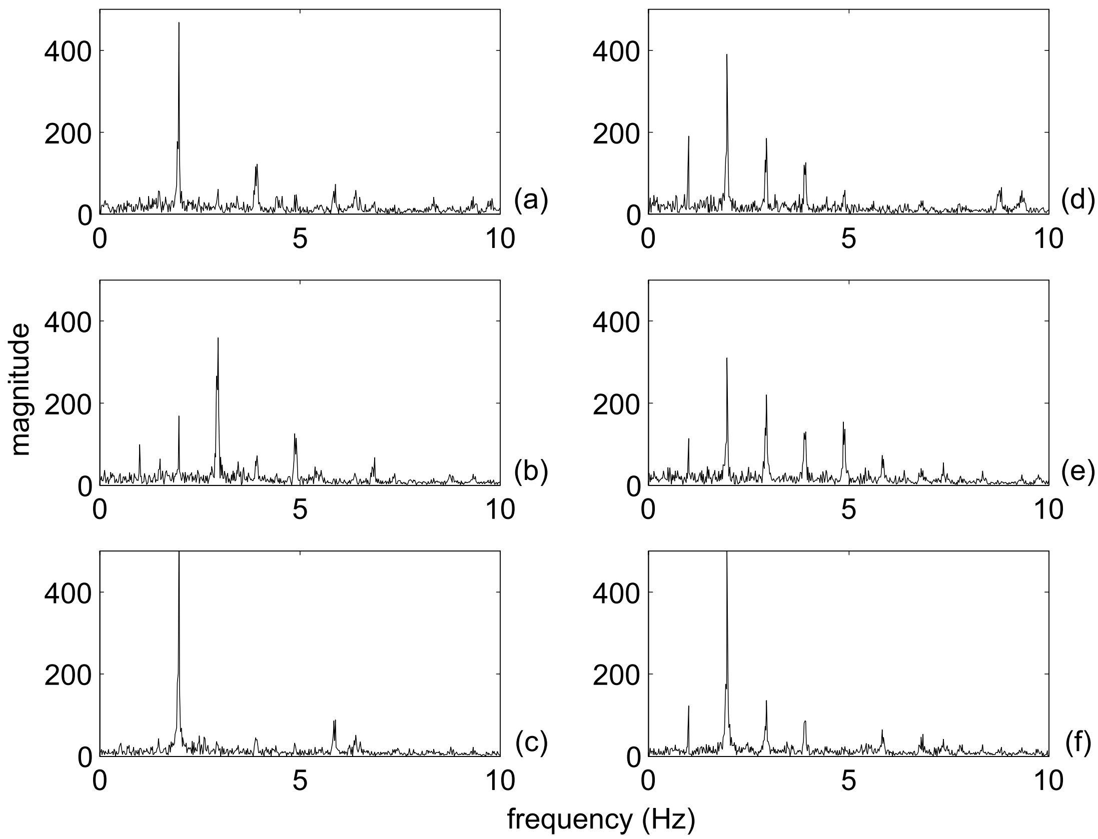


Figure 5.35: Fourier Transforms from a normal subject walking at $5\,\mathrm{km.\,h^{-1}}$. Back TA: (a) x-axis; (b) y-axis; and (c) z-axis signals. Front-right TA: (d) x-axis; (e) y-axis; and (f) z-axis signal.

walking speed, which are shown in figure 5.36.

The relationship between the sets of signals from the back TA and the front-right TA is illustrated in figure 5.37 for one subject walking at $5\,\mathrm{km.\,h^{-1}}$. When the signals from the front-right TA were compared to the signals from the back TA it was found that the signals from the front-right TA were generally larger in magnitude and were noisier than the signals from the back TA. This was reflected in the signal magnitude areas (SMAs), defined to be the sum of the integrals of the moduli of the three acceleration signals, normalised with respect to time (refer to section 3.7). The SMA of the front-right TA was, when averaged across all subjects and all walking speeds, 19% greater than the SMA of the back TA.

In terms of signal components, the main similarities between the two sets of signals were in the vertical signal components, which had similar shapes and were in phase. This relationship between the vertical signals enabled the components of the gait cycle - step rate, single and double support times - to be extracted from

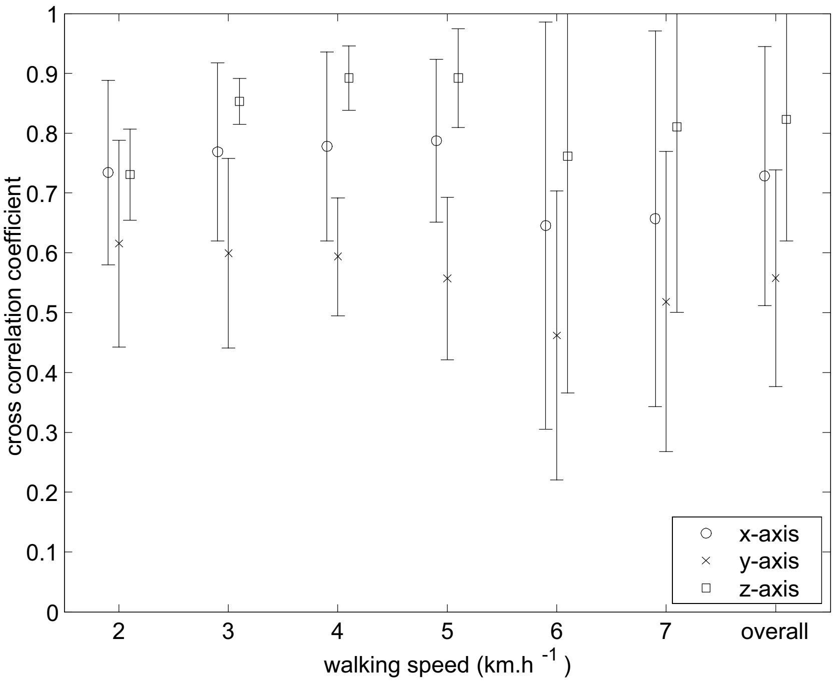


Figure 5.36: Mean cross correlation coefficients between the Fourier transforms of the front-right TA signals and the back TA signals as a function of walking speed. Error bars represent 1 standard deviation.

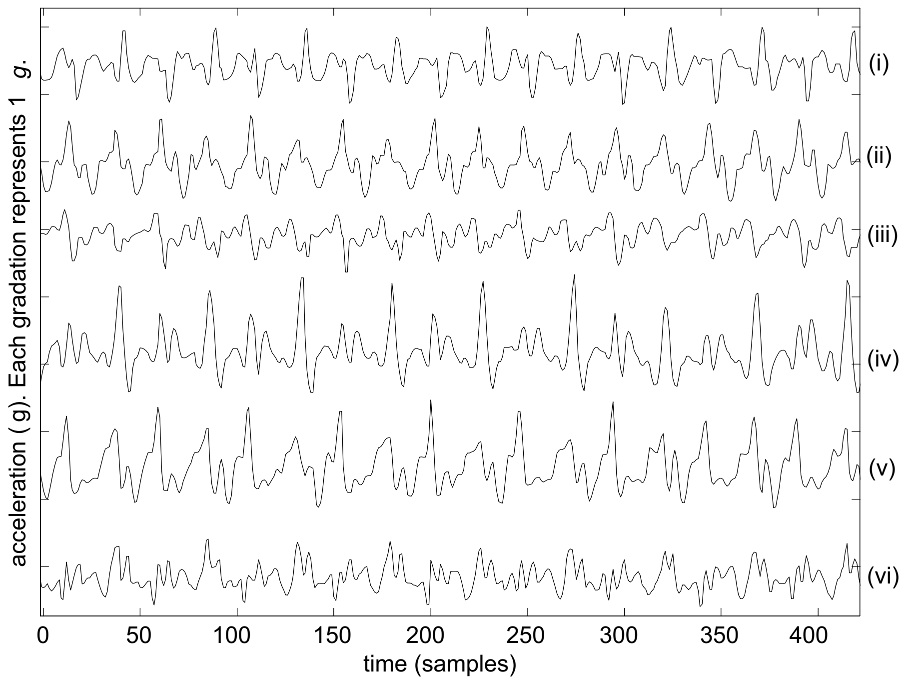


Figure 5.37: The acceleration signals from the two triaxial accelerometers for a normal, healthy subject walking at 5 km. h^{-1}, plotted against time. The top three signals are from the sacrum-mounted TA: (i) y-axis, (ii) z-axis, (iii) x-axis accelerations. The bottom three signals are from the TA mounted above the right anterior superior iliac spine: (iv) y-axis, (v) z-axis, (vi) x-axis accelerations. The signals have been vertically shifted relative to each other.

the front-right TA signal by using the knowledge of where they occurred in the back TA signal.

Discussion

It is important to have an understanding of the relationship between the front-right TA signal and the gait cycle so that the signal can be interpreted in terms of physical gait cycle events. The periodicity of the gait cycle is clearly evident in the signals obtained from the back TA and from the front-right TA. As the signals from both TAs have the same period this can be used to relate the signal components from the two TAs. This is most evident in the timing of the peaks in the vertical acceleration component, which occurred at the same time in both signals. The timing of primary components of the gait cycle - heel strike, heel off, and forefoot strike - can be deduced from the acceleration signals. This allows aspects of the physical gait to be studied using the signals from either a back or a front-right TA.

The gait components may be represented by different events in the acceleration signals from the two TA devices. The different physical placement of the devices mean that the relative magnitude and timing of events in the gait cycle may be seen slightly differently by two TAs. For example, the back TA sees a symmetric gait, but the front-right TA sees a lopsided gait with different magnitude peaks occurring between the right and left foot steps. The overall period remains the same but the internal gait cycle timing is shifted. This means that the front-right TA signal cannot be used directly to make inferences about the symmetry of the gait. It could be used directly to measure *changes* in the symmetry for a given subject over time, but further work is needed to model the pelvic accelerations so as to calculate the offset in the timing due to the asymmetric placement of the TA before it can be used for absolute left-right gait symmetry analysis.

It may well be that a measured change in gait symmetry is sufficient to warrant a clinical assessment of gait and that the absolute magnitude of the asymmetry is less important than the fact that the gait is changing. However, if longitudinal unsupervised monitoring of gait symmetry is required, then this can be accomplished by first, in a clinical setting, assessing left-right gait symmetry using a sacrum-mounted TA and simultaneously measuring with a TA attached at the subject's preferred location. This gives a baseline signal. The gait signal from the TA worn during the unsupervised monitoring period can be compared to the baseline signal and any changes in gait symmetry computed, thus giving a measure of the magnitude of the asymmetry.

Research with sacrum-mounted TAs has also identified characteristics of certain pathological gaits in the TA signal. Further work is required before this can be done with the front-right TA and before it can be determined to which gait characteristics the signal is sensitive, but the results of this study suggest that it is also feasible.

It is important to have an understanding of the relationship between the walking signals obtained at different placements around the waist in order to account for the variability of placement that occurs in an unsupervised home monitoring environment. However, the complexity of the gait limited the applicability of the simple models that were investigated in this study.

The cylindrical model resulted in cross correlation coefficients between 0.6 and 0.8 on the x- and z-axes at comfortable walking speeds. These values indicate that, although the details of the two signals differ, the underlying shape of the front-right and back signals is the same, and that the two signals are in phase. However, it failed to obtain any significant correlation between the y-axis signals, and the correlation in the x- and z-axis signals deteriorated at very fast and very slow walking speeds, respectively. This indicates the presence of significant levels of rotational motion, as well as translational motion, in the signal. The relative amounts of rotational motion are dependent on the walking speed.

The higher z-axis correlations suggest that the bulk of the vertical acceleration component is derived from translational motion, rather than rotational motion. The lower cross correlation values on the x- and y- axes suggest that there is a significant component of rotation present here, i.e. rotation about the z-axis, particularly at high and low walking speeds. This is consistent with studies that have found that the rotational displacement about the vertical axis is around twice that of the rotational displacement about the other two axes [174, 209].

The cross correlation coefficients were also affected by the presence of different amounts of movement at the two locations. There were two reasons for this. Firstly, there was more artefact at the front right location than at the back as there is more soft tissue at the front of the body than at the back. Secondly, the front-right of the pelvis actually undergoes more movement than the centre of the back of the pelvis. The centre-back lies on the x-axis and so is not affected by rotations about this axis, but the front-right location is affected by all rotational movements. The extra movement at the front-right location is reflected in the larger SMA at this location.

The adapted displacement model incorporated rotational movement as well as translational movement across the pelvis. This type of model has provided excellent results in terms of representing the displacement of the pelvis during walking. However, it performed poorly in this study when adapted to predict accelerations. It was able to predict phase relationships between the signals at a given placement, but it failed to capture the sharp acceleration peaks and troughs, or the local turning points and inflexions in the signal.

The discrepancy between the excellent performance on displacement and the poor performance on acceleration can be attributed to the act of differentiation, in which noise in the signal is amplified. This has the result that two very similar displacements can give rise to substantially different accelerations.

Under ideal conditions the position signal can be twice differentiated to give an estimate of the acceleration that is within 1–3% of the measured acceleration. This was demonstrated by Ladin *et al.* [131] who used a mechanical rig to produce a sinusoidal displacement. They measured its displacement and acceleration. The position signal was smoothed and differentiated twice. The acceleration signal was known to be a sine wave and so the measured signal was replaced by the function $Y = C + A\sin(2\pi ft + \beta)$ where the parameters were chosen for best fit. The results were then compared and a high accuracy was achieved. The limitation to this approach is that it requires a priori knowledge of the theoretical acceleration signal and it does not take into account real measured deviations in this signal.

Even the smallest amount of noise in the displacement measure can lead to very different accelerations. To demonstrate this point a simulation was undertaken in Matlab. One period of a sine wave with unity magnitude was generated with 1000 samples and double-differentiated. Next random noise was added to the sine wave. The random noise was uniformly distributed in the interval $(-10^{-4}, +10^{-4})$. Both signals were double differentiated. The results are shown in figure 5.38. Visually, the two displacement curves cannot be distinguished, yet there is little similarity between the two acceleration curves. The addition of higher frequency components adds sharp turning points to the displacement signal which result in large accelerations.

Even without the addition of noise, small differences in displacement can have a large effect on acceleration. This is a well known problem in the mechanical engineering discipline of cam design, where both the displacement path and the acceleration path of the cam need to be considered in the design process. Figure 5.39 shows a comparison between three very similar displacements and their resultant acceleration characteristics.

It is clear from this study that the models that are adequate for description of pelvic displacement during gait cannot be applied to describe the acceleration characteristics during gait due to the problems described. Neither is the simple cylindrical model sufficient for modelling gait. If the characterisation of gait by means of accelerometric models is required then further work with detailed analysis

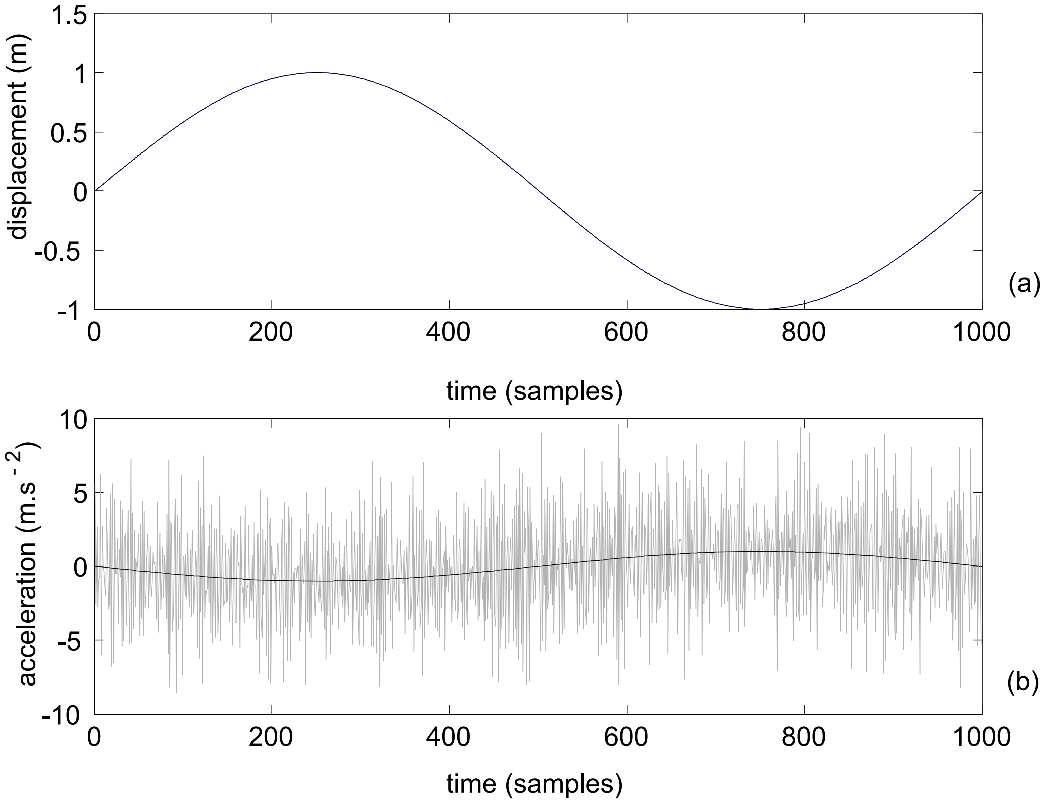
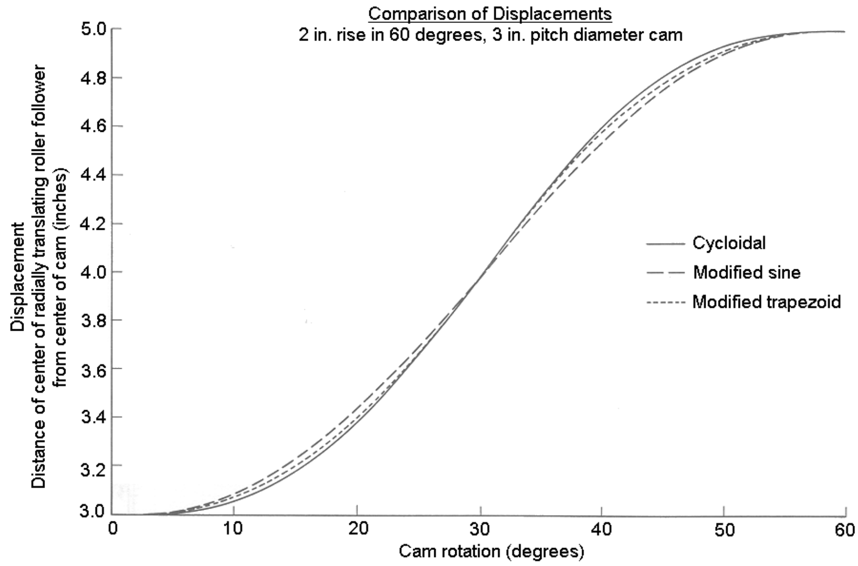
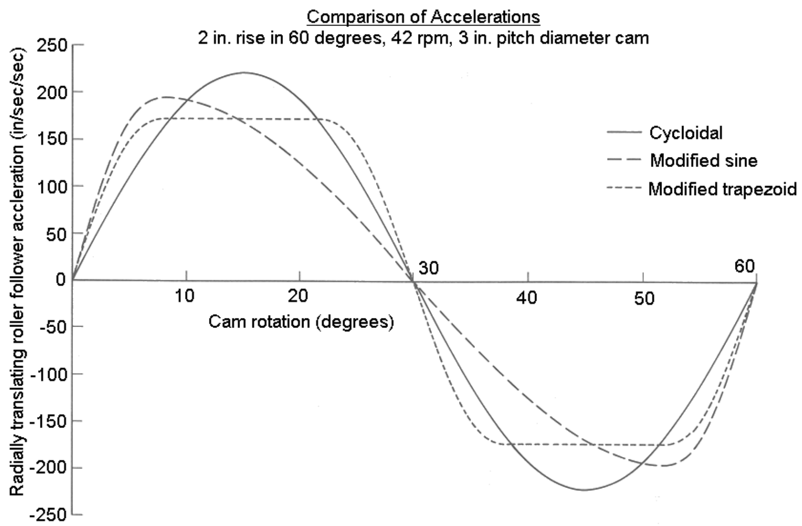


Figure 5.38: Effect of a small amount of noise on the second derivative of a signal. (a) Displacement of a clean sine wave and of a sine wave with a small amount of noise added. The difference between the two waves cannot be detected visually. (b) The accelerations of the two sine waves, calculated by second order differentiation. The smooth line in the middle is the acceleration of the noiseless signal, the other is the noisy sine wave acceleration.



Courtesy of Jon Thoreson, 3M Company, St. Paul, MN.

(a)



Courtesy of Jon Thoreson, 3M Company, St. Paul, MN.

(b)

Figure 5.39: Comparison of cam displacements and accelerations. (a) Comparison of displacements. 2 in. rise in 60 degrees, 3 in pitch diameter cam. (b) Comparison of accelerations. 2 in. rise in 60 degrees, 42 rpm, 3 in. pitch diameter cam. Reproduced from Erdman and Sandor [69].

in a gait laboratory is required for the development of deterministic or statistical models.

It is also evident from this study that the internal magnitude and timing of the gait cycle components is dependent on device placement, and so if a precise knowledge of these components is required for a subject, it is important that the placement of the TA does not change over time.

However, in terms of the objectives of this study, it was found that there is a clear relationship between the signals at the two locations during walking. This relationship can be seen in the period, the signal frequency components and in the z-axis signals. Characteristics of gait can be seen and measured in the signals from a front-right TA. Although the asymmetric placement of the device limits its ability to provide absolute measures of the symmetry of the gait, relative changes could be measured directly from the signal.

Conclusion

The relationship between signals obtained from a TA placed at the back of the waist and a TA placed at the front-right of the waist during gait was investigated. Simple models relating the two were evaluated, and the signals obtained were compared to published results.

Gait contains a substantial rotational movement and this meant that walking could not be adequately modelled by a simple translational model. The cylindrical model resulted in a moderate correlation on the x-axis at comfortable walking speeds, but resulted in little correlation between the y-axis signals due to the presence of rotational movement.

Displacement models use six fully decoupled degrees of freedom, each moving with sinusoidal motion. These models provide accurate models of pelvic displacement during walking but cannot be adapted to estimate accelerations due to the amplification of artefact and error during the differentiation process.

Parameters of gait can be identified in the signals obtained from a TA attached at the waist above the right anterior superior iliac spine, by comparing them to the signal obtained from a TA attached at the back of the waist, where the characteristics that identify events within the gait cycle are known. This makes feasible the use of the waist-mounted TA device for the study of gait during routine daily activities in an unsupervised setting over extended periods.

The signals from the back TA and the front-right TA shared the same frequency components, although Fourier transform analysis showed that the harmonic frequencies occurred in different proportions between the two TAs. The z-axis (vertical) components were the most similar, being in phase and having correlation coefficients between 0.6 and 0.8. As a result, the step rate and the step rate variability can be identified directly from the signal of a front-right TA by finding a fiducial reference point in the signal and measuring the time between repetitions.

The details within the signals differed between the two TA placements. It appears that the signal features that represent events within the gait cycle differ at different placements. Further work is required before parameters that measure components within the gait cycle, including single and double stance times, can be confidently identified using only the signal from a TA attached above the anterior superior iliac spine.

5.4.7 Summary

The TA output of a body worn TA is dependent on

- the movement being performed;
- the postural orientation of the body;
- the placement of the device on the body; and
- the orientation of the device relative to the body.

The preferred placement for the TA unit was found to be above the anterior superior iliac spine. Subjects found this placement comfortable, the unit and its push button could be easily reached but were unlikely to be knocked, and the unit was against the bony matter of the pelvis which reduced artefact due to soft tissue movement. However, in an unsupervised setting, the exact positioning will depend on personal preference, body shape and choice of clothing.

A waist-mounted TA device attached to a stationary subject was found to be well-modelled by a TA attached with the same orientation to the curved face of a regular cylinder. This model could predict the TA output of a subject in a known postural orientation with a mean error of less than $0.26g$ for any placement about the waist.

The same cylindrical model was applied to model the TA output during the sit-stand-sit movement. Two TA units were simultaneously attached to a subject; one above the sacrum, the other at various locations on the front and sides of the waist. The model was used to transform the front TA signal to predict the back TA signal. The mean error between the predicted and measured signals was

$8.1 \pm 5.4\%$, indicating that this very simple model provided a good representation of the relationship between the signals obtained around the waist in the movement. This is due to the bilateral symmetry of the stand-to-sit and sit-to-stand movements, which means that most of the movement is translational rather than rotational.

In contrast, walking has a substantial rotational movement and cannot be adequately modelled by a simple translational movement model in which the waist is modelled by a cylinder. Biomechanical displacement models use six fully decoupled degrees of freedom, each moving with sinusoidal motion. These models provide accurate results in terms of displacement during walking but cannot be applied to estimate accelerations due to the amplification of errors during the differentiation process.

When signals from a TA attached at the back of the waist and one attached above the right anterior superior iliac spine were compared during treadmill walking they were found to contain the same frequency components and there was a high correlation between the two z-axis signals. This allowed temporal features between the two signals to be compared. Previous studies have shown that parameters of the gait cycle can be identified from the signals of a sacrum-mounted TA. This study found that those same parameters can also be identified from the signals of a TA placed at the waist above the anterior superior iliac spine.

Parameters of step rate and variability can be determined from the signal of the TA placed at the front of the waist signal alone, but further work is needed before parameters within the gait cycle such as single and double stance times can be confidently identified using only a TA placed at the front right of the waist. This is due to the differences in signal characteristics that occur at different locations on the waist, and also to the amount of variation in walking style between individual subjects and different walking speeds.

5.4.8 Conclusion

If the TA device placement is known then postural orientation can be computed and sit-stand-sit movements can be directly compared to those carried out by different subjects, and by the same subject on different occasions by means of a simple transformation. Thus, for resting states and sit-stand-sit movements, important characteristics can be identified from the signal of a TA placed anywhere on the waist.

In walking, the step rate can be identified from the signal of a TA placed anywhere on the waist. However, walking is a complex motion that contains a significant level of rotational movement, and its accelerations at the pelvis were not able to be modelled using a simple deterministic model. Characteristics within the acceleration signal are dependent on placement of the device. In order to be able to systematically identify parameters from within the gait cycle, a better understanding of the signals from a given placement is required.

In the same way that postural orientation can be inferred from the signal if the placement is known, the device placement can be deduced from the signals produced in known orientations. A simple procedure in which the subject stands and then lies supine is sufficient to determine the angle of placement, t, of the underlying model, and thus, to establish the placement of the device on the waist. Once this is known the process can be reversed, postural orientations can be determined and activities can be identified and monitored using the TA signals.

5.5 Measuring Physical Activity

5.5.1 Introduction

Accelerometry appears to provide a valid means of estimating metabolic energy expenditure (EE) in free-living subjects and accelerometers have been used successfully in studies to measure physical activity levels during daily activities. Bouten *et al.* [31] found that the sum of the area encompassed by the magnitude of each of the three accelerations from a TA provided a good overall predictor of EE during daily activities. This predictor was normalised and employed in the current work, where it is referred to as the (Normalised) Signal Magnitude Area:

$$A = \frac{1}{t} \times \left(\int_0^t |x(t)|\, dt + \int_0^t |y(t)|\, dt + \int_0^t |z(t)|\, dt \right), \tag{5.20}$$

where x, y and z are the acceleration signals from each of the accelerometers with respect to time, t. A has units of $\mathrm{m.\,s^{-2}}$. The magnitude of the SMA obviously depends on the size and nature of the signal. The signal preconditioning (in particular, the median filtering) must therefore have an effect on the SMA. The magnitude of the SMA also depends upon the placement location. However, although the optimal regression parameters must change, Bouten *et al.* [32] found that there was a high correlation between SMA and EE, whether the TA was placed on the low back, shin, upper leg, trunk, lower arm or upper arm.

In this section, studies were conducted in order to understand the changes imposed on the SMA by the chosen signal conditioning processes and by the chosen device position. The first study investigated the effect of median filtering on the SMA. The second study investigated the effect of device placement on the SMA.

5.5.2 A Study of the Effect of Median Filtering on the Signal Magnitude Area

Introduction

A median filter was used to precondition the signal in order to remove noise spikes (refer to section 5.2.3). The purpose of this study was to investigate the effect of median filtering on the SMA.

Experimental Procedure

Four data sets were used in this study.

1. 26 normal subjects carried out a routine in the laboratory in which they stood, sat in a variety of chairs, walked along a corridor, and walked up and a flight of stairs. The TA was placed at the waist, above the right superior anterior iliac spine. The experimental procedure is described in detail in section 6.5.

2. Two elderly subjects carried out an unsupervised, directed routine in their homes. The routine consisted of standing, sitting, walking and lying. The TA was worn at the front of the waist, but the exact location was left to each subject's preference. The routine was repeated 21 times by each subject, with each repetition being carried out on a different day. The data were taken from the set of data collected in the experimental procedure described in section 7.8.

3. Data were collected from 12 healthy subjects walking on a treadmill at various speeds. The TA was placed at the waist, above the right superior anterior iliac spine. The experimental procedure is described in detail in section 5.4.6.

4. Data were collected from 6 unsupervised, elderly subjects while they were carrying out their usual daily activities in their homes. The TA was worn at the front of the waist, but the exact location was left to each subject's preference. Each of the data samples encompassed a 2.5 hour period. Four of the six data sets were noisy, due to the subjects moving in and out of range of the TA receiver unit, and this led to some interference in the transmitted signal. These data were taken from the set of data collected in the experimental procedure described in section 7.8.

Data Processing

The body movement acceleration components from each subject were extracted, using the FIR separation filter described in section 5.2.7. The SMA was calculated for each subject over the duration of the test.

The raw acceleration signals were then median filtered using filters of lengths 3, 5, 7, 9, ..., 45 samples and the above process was repeated.

Results

Increasing the length of the median filter caused the SMA to decrease monotonically. The curve produced in each test was well-fitted by a quadratic or cubic function. This is illustrated in figure 5.40a which shows the mean SMA for the 26 subjects who carried out the basic daily activities routine. A quadratic curve is fitted to the data, and the residuals between the model and the experimental data are shown in figure 5.40b. It can be seen that the SMA reduces to around 75% of the raw value by the time that the median filter reaches a length of 7 samples.

Figures 5.41 to 5.44 show the mean SMA, plotted as a percentage of the unfiltered SMA, as a function of median filter length for the other three data sets. The results for the elderly subjects performing the directed routine were very similar to those for the younger subjects. The values of the SMA, averaged over all routine repetitions across both elderly subjects are shown in figure 5.41. Again, the SMA reduced to around 75% when the filter length reached 7 samples.

The treadmill walking data set yielded a curve with the same shape, but with a slightly steeper profile. When the applied median filter had a length of 7, the mean SMA was 68%. This is shown in figure 5.42.

In the data set from the free-living subjects, the mean SMA dropped sharply between the raw SMA and the filtered SMAs, but then the profile was flatter across the filtered SMAs than in the other data sets (figure 5.43). There was a large variability in the SMA values across the subjects. Individual filtering effects are plotted in figure 5.44. When a median filter of length 7 was applied, the SMA ratios ranged from 44% to 72% between subjects, a range of 28%.

The SMA data from the six subjects are also presented as a percentage of the filter length 3 SMA data in figure 5.45. The rate of decay in these SMA ratios was very similar across all subjects. The range of these SMA ratios increased from 5% when the filter length was 5 samples to reach a maximum of 10% when the filter length was 23 samples.

All six of the free-living subjects spent over half of the data collection period

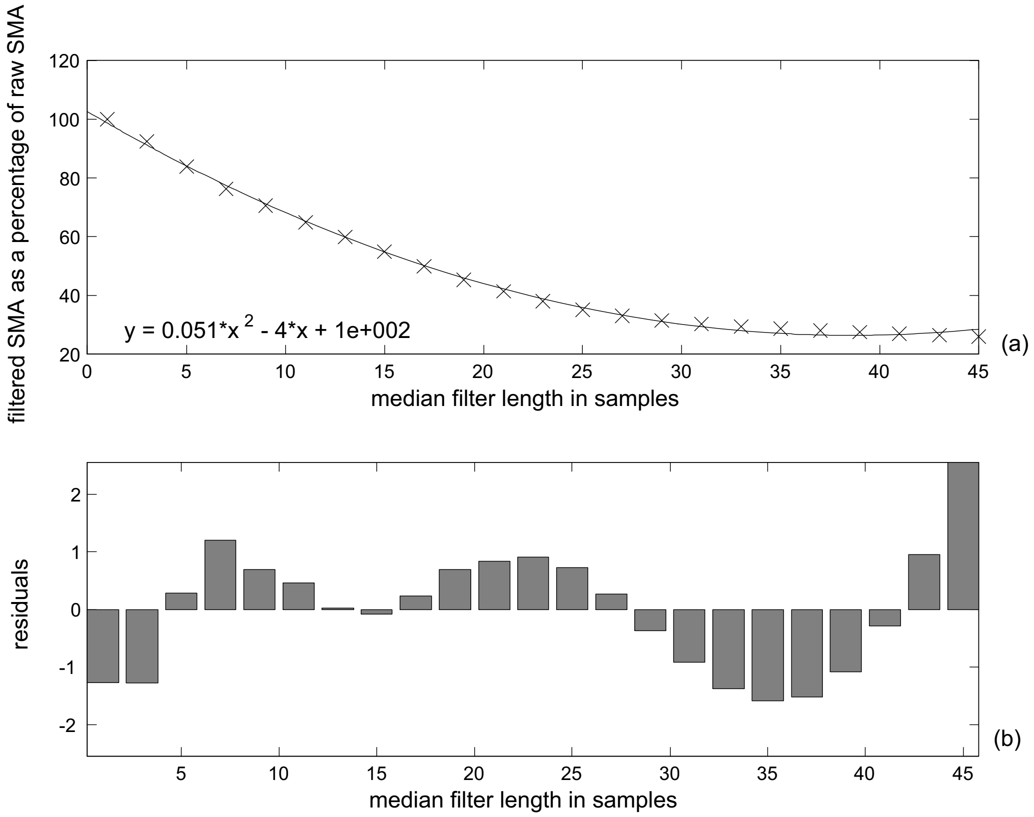


Figure 5.40: Effect of median filter length on signal magnitude area during basic daily activity for the 26 healthy subjects carrying out the directed routine. (a) Mean SMA plotted as a percentage of the unfiltered SMA. The data is well fitted by the decreasing portion of a quadratic curve, $y = 0.051x^2 - 4x + 100$. (b) Residuals between the quadratic curve and the data.

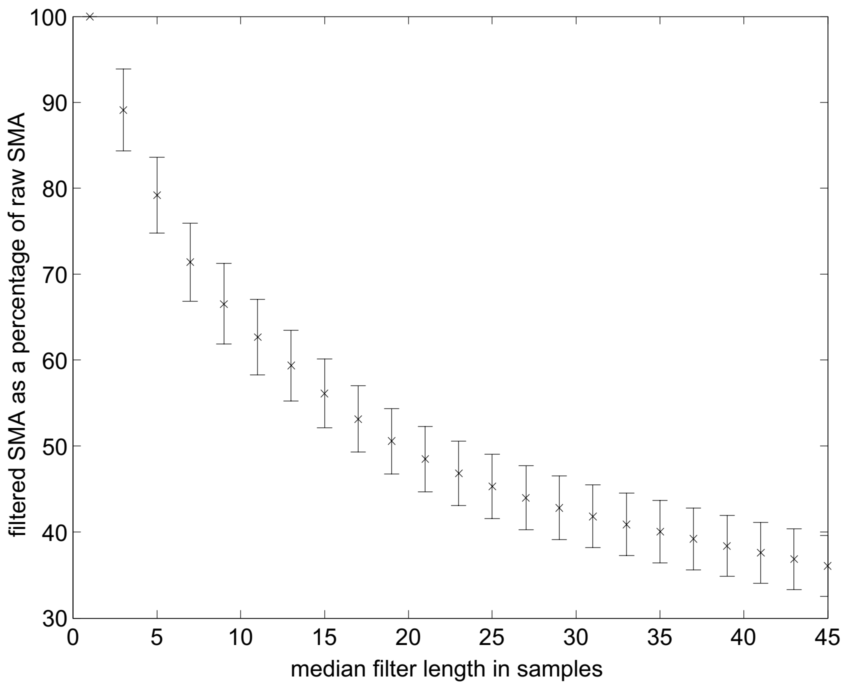


Figure 5.41: Effect of median filtering on the signal magnitude area for data taken from two elderly subjects, each performing a sequence of basic daily activities 21 times. Error bars represent 1 standard deviation.

resting. However, subjects 2 and 4 were substantially more active than the other subjects. This led to a large difference in the measured SMAs for the six subjects. The measured SMA values are listed in table 5.5. No correlation was detected between the effect of median filtering and the amount of energy expended, as measured by the raw SMA value.

Discussion

A sharp drop was observed in the SMA ratio curves between the raw and filtered (length 3) signals for the free-living subjects. This effect occurred because the median filter filtered out the noise spikes in the signal. During the data collection period, subjects moved in and out of range of the TA signal receiver and consequently, large noise spikes occurred in the signal. These caused an artificial increase in the measured SMA. This effect was largely removed when the median filter was applied to the signal. In this case, the filtered signal gave a better estimate of the SMA than did the raw signal.

When the subsequent SMA values were compared to the filtered (length 3) signal the curves were very similar across all subjects, and the curves reduced more slowly

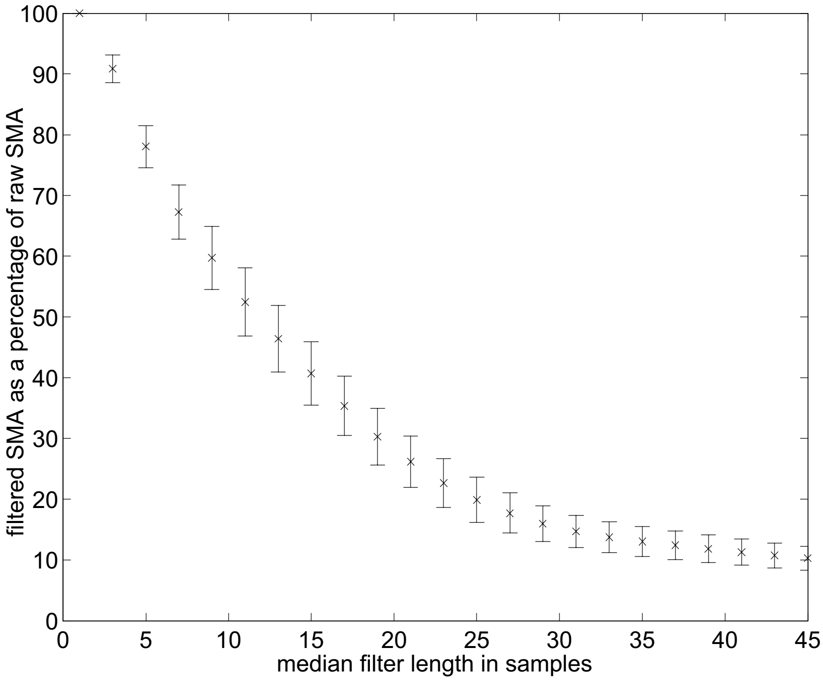


Figure 5.42: Mean effect of median filter length on signal magnitude area during treadmill walking at various speeds by 12 subjects. Error bars represent 1 standard deviation.

Subject	**Raw SMA** ($\times 10^{-3}g$)	**SMA, filter length 3** ($\times 10^{-3}g$)	**SMA, filter length 7** ($\times 10^{-3}g$)
1	58	32	26
2	181	132	112
3	78	41	34
4	173	141	123
5	84	51	44
6	31	27	22

Table 5.5: Measured SMA values for each of the 6 elderly free-living subjects.

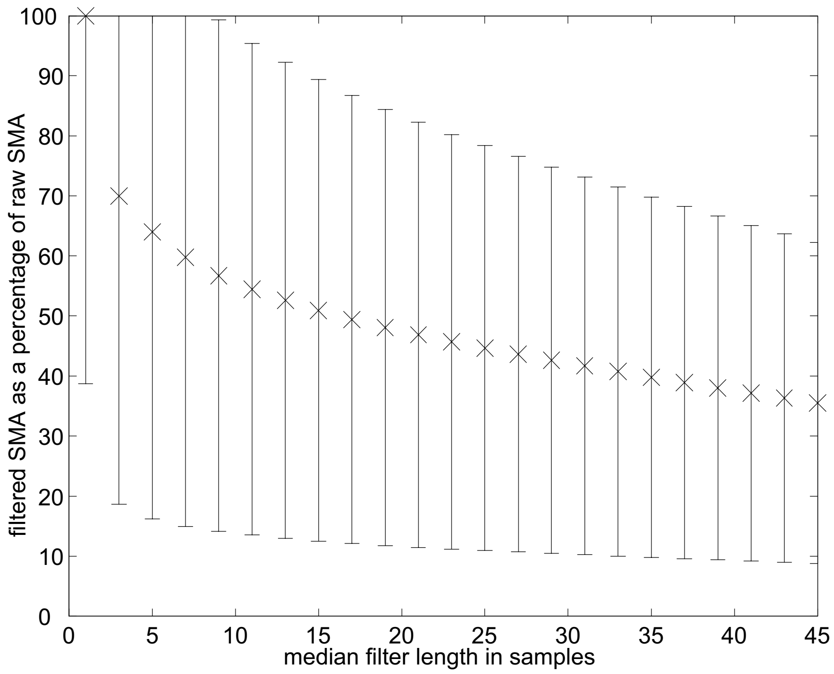


Figure 5.43: Mean effect of median filter length on signal magnitude area during daily activity in 6 free-living subjects. Error bars represent 1 standard deviation.

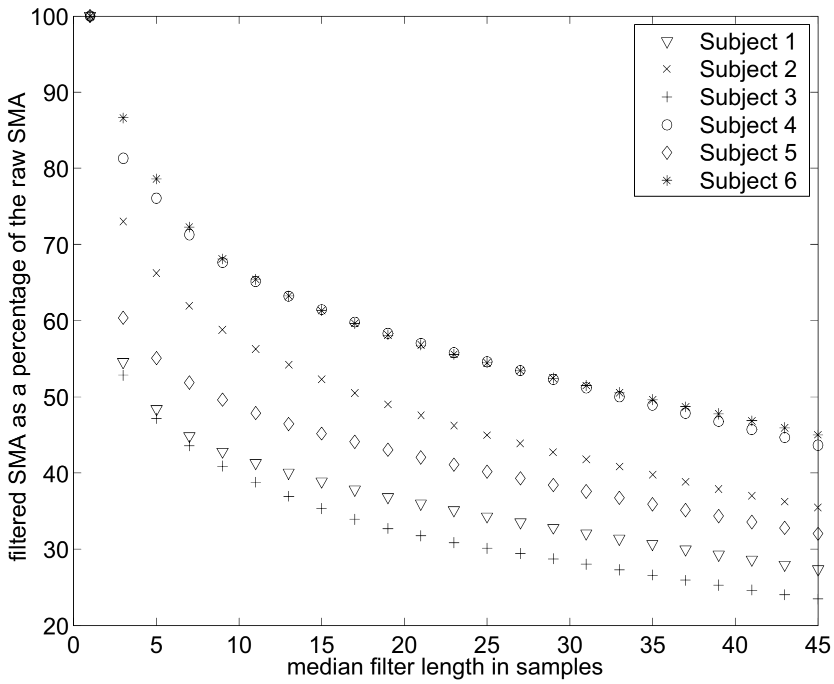


Figure 5.44: Effect of median filter length on signal magnitude area for each of the 6 free-living subjects.

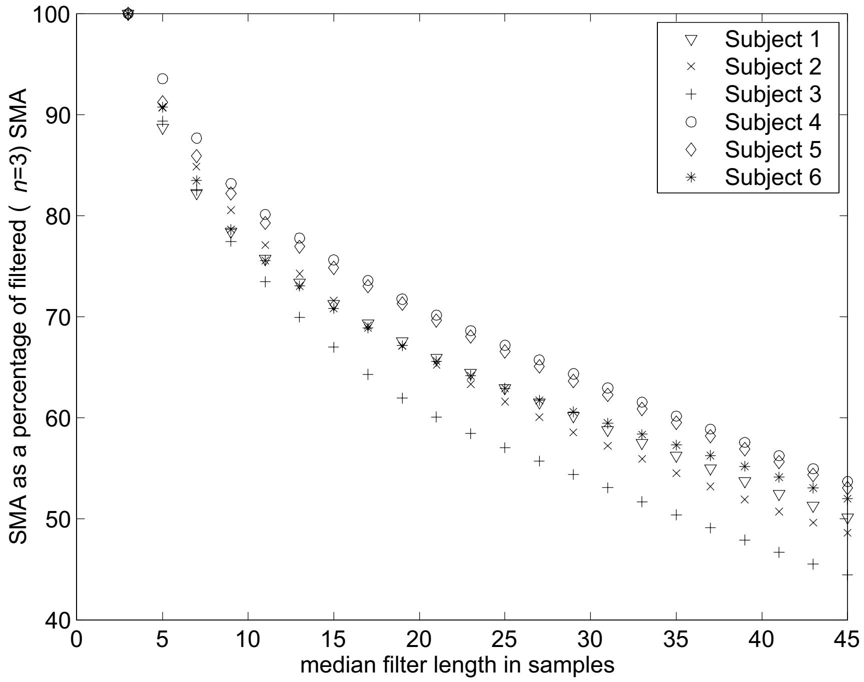


Figure 5.45: Effect of median filter length on signal magnitude area for each of the 6 free-living subjects, shown as a percentage of the filtered ($n = 3$) SMA.

than for the other data sets. This was because all of the subjects spent more than half of the data collection period resting. When a subject is resting there is little change in the TA signals, and so the median filter has little effect. The median filter has the greatest effect when the subject is engaged in vigorous activity. In this study, the data set of treadmill walking contained the most vigorous activity and as a result, it has the steepest ratio curve.

The treadmill walking data set consisted of walking at speeds between 2 and 7 $\mathrm{km.\,h^{-1}}$. The upper walking speeds were more vigorous than would be expected from housebound subjects. Therefore, the effect of median filtering on the measured SMA of unsupervised routine daily activity should be bounded by its effect on the treadmill walking data. In fact, in the first three data sets, the drop between the raw and first filtered SMA ratios was around 10%, as was the drop between the first and second filtered SMA ratios (filter lengths 3 and 5 respectively). The drop between the second and third filtered SMA ratios was slightly less, and the difference continued to decrease as the filter length increased. In the fourth data set, the drop between the raw and first filtered SMA ratios was much greater due to the presence of noise in the signal, but after this the magnitudes of drops between adjacent SMA ratios were similar to those in the other data sets.

The effect of the median filter decreases as the level of filtering increases because as the signal becomes smoother (due to heavier filtering), further increasing the median filtering has less of an effect.

The consistency in the effect of the median filter on the SMA across data sets from different age groups, postures and activities indicates that a standard adjustment factor can be introduced to account for the effect of filtering on the measured SMA when estimating the metabolic energy expenditure. This adjustment factor is dependent on the filter length. From the results of this study, it may be concluded that the adjustment factor should be around 10% when a filter of length 3 is used, 20% when a filter of length 5 is used, and 25-30% when a filter of length 7 is used. Future research should, if possible, involve a direct comparison of calorimetric and TA monitoring of free-living subjects in order to objectively quantify the accuracy of this model, in which the TA is placed at the front of the waist and the collected data is filtered to remove noise spikes.

Conclusion

It is evident that the effect of median filtering on the SMA cannot be ignored. Even small levels of filtering (filter length = 5 samples) lead to a magnitude reduction of around 20%.

However, the size of this reduction was consistent across data sets from different age groups, postures and activities, suggesting that the effect of the median filter can be compensated for in the coefficients of the regression equation relating SMA to the metabolic energy expenditure.

5.5.3 A Study of the Effects of Device Placement on Signal Magnitude Area During Walking

Introduction

The purpose of this study was to investigate the validity of using the signal from a TA attached at the waist above the superior anterior iliac spine to estimate the metabolic energy expenditure.

Experimental Procedure

Twelve healthy subjects walked on a treadmill for five minutes at each of 2, 3, 4, 5, and $6\,\mathrm{km.\,h^{-1}}$. Each subject wore two TAs. One was attached at the waist above the right anterior superior iliac spine, and one was attached to the back of the waist

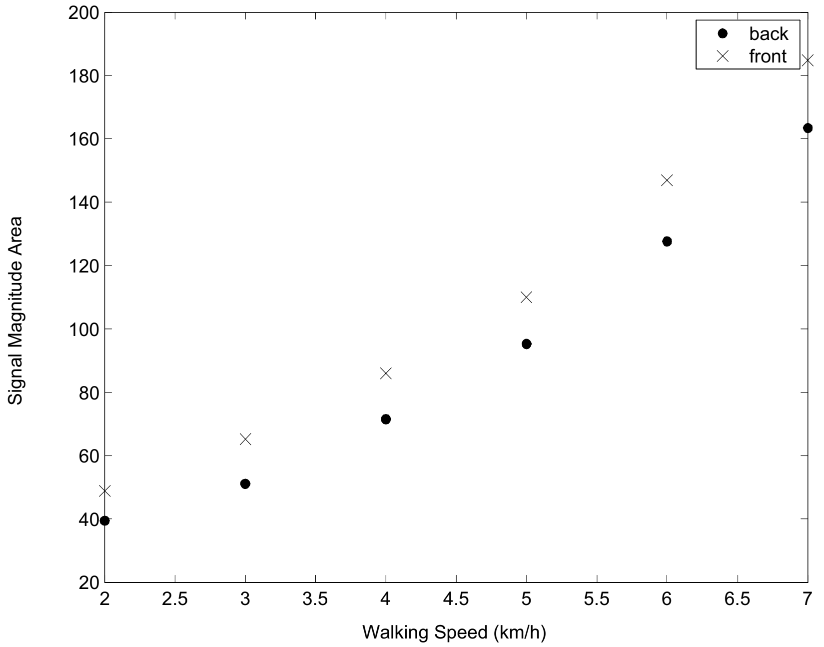


Figure 5.46: A comparison of signal magnitude area between front and back TAs as a function of walking speed across all 12 subjects.

at the spine. Data were logged and time stamped from both TAs during the routine. The experimental procedure is described in detail in section 5.4.6.

Data Analysis

One three-minute period at each speed was chosen for analysis from each subject. Data from the start and end of each five minute walking period were not included in the analysis. Data from the back-mounted TA were used to compute the signal magnitude area (SMA) for each walking speed for each subject over the three minute period. Data from the front-mounted TA were used to computed the SMAs for the same three-minute periods. The results from the two TAs were compared.

Results

Figures 5.46 and 5.47 show the mean SMAs obtained from the two TAs across all 12 subjects.

The ratio of the two sets of data (front TA SMA / back TA SMA) is approximately constant across the range of walking speeds (figure 5.47). The SMA from the front-mounted TA was, on average, 19% (±5.6% standard deviation) greater than

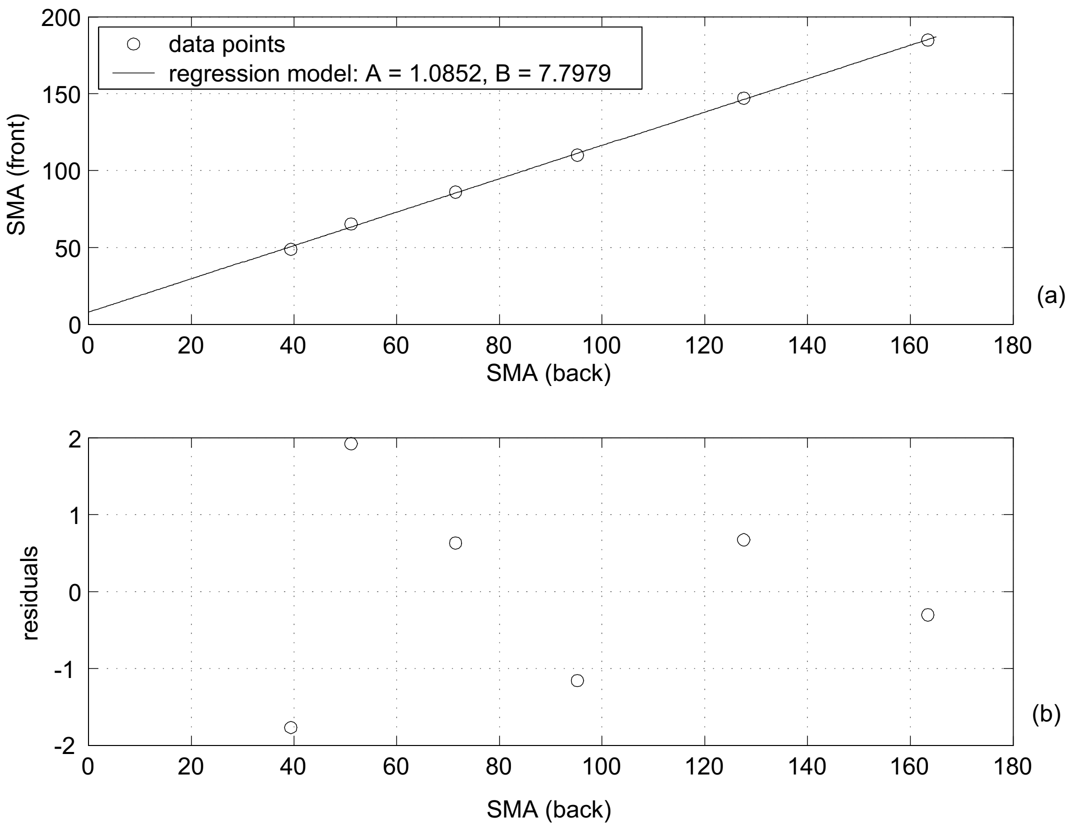


Figure 5.47: SMA (front) versus SMA (back). (a) There was linear relationship between the SMA at the front placement and the SMA at the back placement. Regression model: $SMA_{front} = A \times SMA_{back} + B$. (b) Regression residuals.

the SMA from the back-mounted TA. The r^2 correlation statistic for the regression was 0.9993, indicating that the two SMAs were almost perfectly linearly correlated.

Discussion

The SMA measured by a TA placed at the back of the waist has been found to be a reliable estimator of energy expenditure [31, 34]. Moreover, simulations have shown that this should also be the case for other positions on the body [32], although the regression parameters depend on the TA device placement location. The findings of this study were in agreement with this result, as indicated by the very strong linear correlation between the two.

Comparing the SMA from the front-placed TA to the SMA from a TA placed at the back, which is known to be a reliable estimator of energy expenditure, allowed the quality of the estimates provided by the front-placed TA to be assessed without using specialised calorimetric techniques.

Conclusion

From this study it can be concluded that the metabolic energy expenditure can be reliably estimated using a TA attached at the front of the waist, above the right superior anterior iliac spine.

5.5.4 Summary

Median filtering has a significant, but consistent effect on the SMA value obtained from a TA signal. The effect of the filtering cannot be ignored, but can be compensated for by including an adjustment factor in the regression equations.

Bouten *et al.* [32] determined that good estimates of energy expenditure could be obtained from a body-mounted TA at the low back, the lower leg, the upper leg, the trunk, the lower arm, or the upper arm, but the best results were obtained at the sacrum, which was nearest to the centre of mass of the subject. In the current work it was found that there was a linear relationship between the SMA measured at the sacrum and the SMA measured above the anterior superior iliac spine during walking. Walking is the most vigorous activity likely to be undertaken by a housebound subject and hence consumes the greatest amount of energy. When a range of routine daily activities were considered, the SMA estimate was most highly correlated during walking [34]. Thus it can be concluded that energy expenditure can be estimated from a TA placed at the waist above the anterior superior iliac spine with approximately the same accuracy as can be obtained using a sacrum-mounted TA, although the optimal regression parameters will differ.

5.6 Chapter Conclusion

This chapter has developed a rigorous understanding of the signals obtained from a waist-mounted triaxial accelerometer (TA) device. The signal has two main components, gravitational acceleration and body acceleration. The gravitational acceleration indicates the postural orientation of the subject, while the body acceleration describes the movement of the subject. The output signal is the vector sum of these two components. As there is frequency and temporal overlap between the two components, they cannot be perfectly separated. Several different methods for approximately separating the components were considered. The most robust method used a FIR low pass filter to compute the gravitational acceleration. This was subtracted from the original signal to obtain an estimate of the body acceleration. The limitation of this method was that it introduced ringing into the signal. A second approach used the magnitude acceleration, ρ. Instead of using a low pass filter the gravitational acceleration was estimated from the acceleration magnitude signal during periods of rest, using splines. This method did not introduce any ringing into the system but it did not perfectly remove the d.c. offset from the body acceleration component signal. The two methods are appropriate in different circumstances. The filter method is appropriate when removal of the d.c. component is important, such as in the estimation of metabolic energy expenditure. The spline method is more appropriate when distortion of signal characteristics is not acceptable, such as when accurate identification of activity endpoints is required.

The acceleration data can be represented in either Cartesian or spherical coordinate form. The two representations are isomorphic but highlight different aspects of the data. As the body acceleration cannot be completely separated from the gravitational acceleration, integrating the body acceleration component does not provide accurate estimates of velocity or displacement.

The TA device that was described in chapter 4 has a high signal to noise ratio, and this ratio is further improved by filtering the signal (using a median filter) to remove noise spikes that were added to the signal during RF transmission. This device was used to study the effect of device placement on the TA signals obtained.

The preferred placement for the TA unit was found to be on the waist above the anterior superior iliac spine. However, the exact positioning of the unit in an unsupervised setting will depend on subject preference, body shape and choice of clothing. A simple model can be used to relate TA signal output, postural orientation and TA placement. If any two are known then the third can be deduced. Thus, in the unsupervised setting, a known routine of postures can be used to determine the placement of the TA unit. This knowledge can then be used during free movement to identify postural orientations.

The same model can be used to relate TA outputs from different placements at the waist during sit-stand-sit movements. This allows movements to be directly compared, even if they were not undertaken with the TA at the same placement. This is important for longitudinal monitoring of parameters of the movement through unsupervised monitoring.

This model did not extend to walking due to the presence of rotational movement. Neither could a simple model that reliably models displacement be adapted to model accelerations because of the amplification of errors during the differentiation process.

Events within the gait cycle were characterised by different signal features from TAs at different placements on the waist. Therefore, in order to determine parameters within the gait cycle, such as single and double stance times, it is necessary to know the placement of the device and to understand the relationship between events in the gait cycle and the features of the signal at that point. However the same frequency components are measured at different placements on the waist and there is a high correlation between the vertical (z) axis signals at moderate walking speeds and so parameters such as cadence and step rate variability can be determined from different waist placements.

Consequently, a system for monitoring postural orientation, sit-to-stand movements and parameters of step rate during walking can use a waist mounted TA placed above the anterior superior iliac spine and can tolerate variations in the placement position, both across subjects and for the same subject over time.

Metabolic energy expenditure can also be estimated by a TA placed above the right anterior superior iliac spine with the same degree of accuracy as can be obtained using a TA placed at the sacrum.

In the next chapter this understanding of the signals is used to develop a framework for identifying and classifying postures and activities from the signals obtained from a waist mounted TA. Algorithms are developed to test for important postures and activities, and to extract relevant parameters.

Chapter 6

Interpreting the TA Signal

6.1 Overview

In the last chapter the nature of the signals produced by a waist-mounted triaxial accelerometer (TA) were discussed. The signal is made up of two components, a gravitational acceleration component that provides information on the postural orientation of the subject, and a body acceleration component that provides information on the movement of the subject.

The purpose of using a TA in an unsupervised setting is to monitor parameters with clinical relevance. In order to achieve this, the TA signals need to be interpreted in the context of the movements that are being undertaken by the subject.

In this chapter techniques are developed for identifying important signal components and extracting relevant information. The signal interpretation and information extraction takes place within an organised, hierachical framework for data processing and interpretation. The framework is structured as a binary tree classifier in which decisions ripple down the tree from node to node until a final decision is reached. The classifier distinguishes between activity and rest, between the various states of rest, and identifies falls, walking and transitions between postural orientations. Once a state is identified, relevant parameters are extracted from the data.

The first part of this chapter discusses the framework as a whole. The subsequent sections describe the details of each component of the classification system. In these sections algorithms for identification, classification and parameter extraction are developed and evaluated. Each algorithm that was developed for implementation within the classification framework was evaluated using experimental data obtained from a cohort of normal subjects in a laboratory setting.

6.2 A Framework for Movement Classification

Ambulatory monitoring of a free-living, housebound subject serves a twofold purpose. Its first purpose is to detect adverse events (such as falls) so that the alarm can be raised. Its second purpose is to provide longitudinal tracking of clinically relevant parameters. Both of these requirements place constraints on the way in which the data are processed.

The data must be processed in close to real-time conditions in order to achieve timely event detection. Real-time processing also has advantages for longitudinal tracking of parameters in that it can reduce the data storage requirements. A data capture rate of 45 samples.s^{-1} leads to a data capture rate of more than 40 megabytes a day. If all of these data were stored for post-processing when particular information was required it would result in large storage space requirements, slow data retrieval times and a large processing capacity requirement. A better approach is to process the data as they are received and then to store only the relevant, processed parameters. This calls for close to real-time processing and for efficient processing algorithms.

Before parameters pertaining to the movement can be extracted from the signal, the movement must be identified. Most of the systems for classification of movement that have been described in the literature have used multiple sensors (section 3.8), and have used methods that are specific to the set of activities being investigated.

Kiani *et al.* [123] presented a more general classification schema based on a decision tree, in which each node had multiple branches. However, the decision at each node was obtained by measuring parameters such as average, norm, and standard deviation and then classifying on the basis of these parameters. This method requires a comparison between the measured parameters and the parameters of all of the possible classifications at that node. Although the tree structure allows a logical flow of decisions, it remains difficult to add or to change activities as this requires modification of an algorithm that makes multiple decisions.

The purpose of the framework developed in the current work is to identify activities and postural orientations from the signals obtained from a single TA unit worn by a free-living subject. Once an activity or postural orientation is identified then relevant parameters can be extracted. This framework also uses a classification tree, but with several significant differences to the one designed by Kiani.

The classifier was designed with a hierachical structure, which is illustrated in figure 6.1. Broad classifications are made in the top levels of the tree, and more detailed subclassifications are made in the lower levels of the tree. Each classification

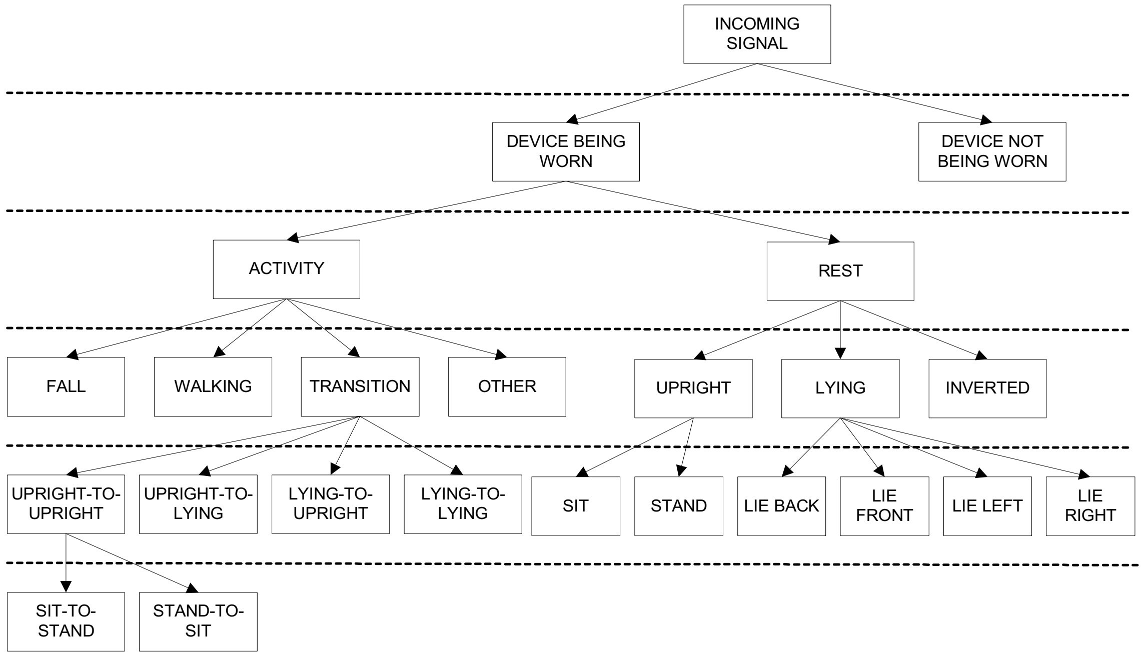


Figure 6.1: Classification hierachy showing the increasing levels of detail within the classifications.

can be further sub-classified until either the required level of detail is reached or the limits of accuracy of the system are reached. For example, an upright-to-upright transition can be sub-classified as either a sit-to-stand transition or as a stand-to-sit transition. A lying-to-lying transition can be sub-classified as one of sixteen sub-transitions based on the starting and finishing postures. For example, the lying-to-lying transition may be a transition from lying supine to lying on the left side.

Although there are multiple activities and postures at the same hierarchical level, the classification framework consists only of binary (yes/no) decisions. If there are more than two possibilities for the classification, then the first possibility is tested. If an affirmative response is returned then this classification is accepted and processing flows down to the next level in the hierarchical tree. If a negative response is returned then this classification is rejected and the next possibility is tested. This process continues until a classification is made. An overview of the logical flow of the process is shown in figure 6.2.

In this approach it is necessary to ensure that there is a fallback case that is accepted if all of the other classification possibilities are rejected. This can be a specific state if all of the possibilities at a given level are explicitly included. For example, a subject is either engaged in activity or is resting. There are no other

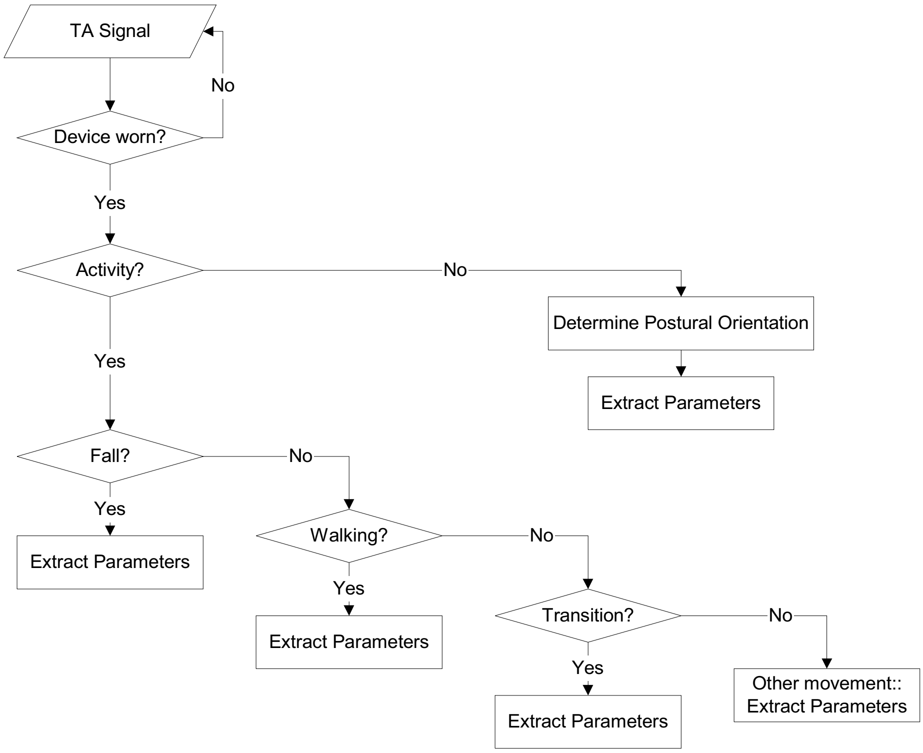


Figure 6.2: Overview of the triaxial accelerometer signal data processing and classification framework.

possibilities. Both of these possibilities are explicitly included in the hierarchical tree. The incoming signal is tested to see whether the subject is engaged in activity. If this is not the case then the subject is classified as resting, which is the fallback case.

The fallback case can also be a generic case that encompasses a range of possibilities where more specific classification is not required. For example, in figure 6.2, if a subject is classified as engaged in activity, then the activity is tested to see whether it is a fall, walking or a transition between postural orientations. There are many other activities that could be undertaken by the subject but individual identification of them was not required for this study. Therefore, activity signals were tested for the three specific types of activity, but if the subject was not engaged in any of these then the activity classification defaulted to the fallback case of "other movement".

A binary decision tree has a number of useful features. Using binary decisions ensures that only one (simple) decision is made at each node. This speeds the processing and allows easy measurement of the reliability of each decision. All decision nodes have exactly two branches which makes the tree easy to read and helps to ensure that no valid logic paths have been inadvertently omitted. The modular "ripple down" approach also makes it easier to maintain the classification tree, to modify or enhance the algorithms to achieve particular processing or decisions, and to extend the tree into further levels of subclassification by adding more branches at the bottom of the tree.

Each set of decision nodes below a particular node perform more specific subclassifications within the more general parent classification achieved by the higher node. The decisions made higher up the tree are more certain than the decisions made further down the tree since any classification uncertainty from the higher branches is transferred to the lower branches.

The most important features of this framework are its flexibility and ease of adaptation. New activities and postures, and new levels of detail can be added to the system without affecting the existing structures, by adding another decision, or layer of decisions, at the appropriate place in the tree. In the following sections, the framework is developed for a particular set of postures and activities, but it can easily be adapted to address other movements and postures as well.

6.3 An Overview of the Signal Processing

Prior research has shown that many clinically relevant parameters can be measured by accelerometry. The current work is concerned with postural orientations of standing, sitting and lying and with activities of walking and transitions between different postural orientations. Each of these movements can provide useful information pertaining to the health status of the subject, particularly in terms of functional ability.

There were a number of steps that needed to be undertaken in order to extract useful information from the TA signal. Before anything could be deduced from the signal, it was first necessary to know that the TA was actually being worn by the subject.

If the TA was being worn then the next task was to decide whether or not the subject was engaged in activity. If the subject was active then the activity was analysed to identify important characteristics. If the subject was resting then the postural orientation of the subject was classified and logged.

Falls, periods of walking and transitions in postural orientation were identified as activities of particular interest. These activities were processed further, and relevant parameters were extracted and stored. Parameters were also extracted and stored for periods of rest.

Different techniques were used at different points in the processing. The decisions were made using a combination of signal processing and heuristics. The decisions higher up the tree, where the decisions were more certain, tended to be decided using only signal processing techniques. Sub-classifications, which could not be determined exclusively from the signal were made using both heuristic knowledge and signal processing techniques. Both fixed-threshold classification and reference-pattern-based classification were applied to identify postural orientations and activities from the signal.

6.4 Is the Device Actually Being Worn?

Introduction

It is important to be able to tell whether or not the device is being worn. In the home environment, it is assumed that the device is either being worn by the subject or has been put down somewhere and is unmoving. If the device is not being worn then the output will resemble that obtained in the static noise tests described in section 5.2.2.

The key to distinguishing between the worn and the unworn TA signals is that human subjects are never completely stationary. There is always some muscle movement occurring and this is reflected in the amplitudes measured on the stationary subject, which are greater than the amplitudes of the completely stationary device.

It was hypothesized that the acceleration signal amplitudes can be used to identify when a TA is being worn. This hypothesis was tested in the following study.

Experimental Procedure

Twenty-six normal, healthy subjects were tested (7 female, 19 male; mean age 30.5 years $\pm$ 6.3 years standard deviation). A TA device was attached to the waist of the subject, above the right anterior superior iliac spine. The subject was asked to stand, as still as possible, for 30 s, then to sit down, as still as possible, for 30 s, and then to lie down, as still as possible, for 30 s.

Data Analysis

Each signal was filtered to obtain the body acceleration signal component, using the FIR filter described in section 5.2.7. From each 30 s signal, the 20 s segment with the lowest root mean square (r.m.s.), calculated on the magnitude vector, ρ, was chosen for analysis. Using these 20 s segments, the r.m.s. was calculated for each of the x-, y-, and z- axes, and for the magnitude vector, ρ. The normalised signal magnitude area (SMA) was also computed for each segment.

The static data signal that was described in section 5.2.2 was used as the basis for comparison between the data from an unworn TA and a worn TA. Twenty-six random samples, each 20 s long, were taken from this static data signal. These were processed in the same way as the data from the worn TA.

The student t-test was used to compare the data from the worn TA to the data from the unworn TA. The x-axis r.m.s. data from when the subjects were lying was compared to the x-axis r.m.s. data from the static data set, the y-axis r.m.s. of the lying data set was compared to the y-axis r.m.s. of the static data set, and the z-axis r.m.s. of the lying data set was compared to the z-axis r.m.s. of the static data set. The standing and sitting data sets were treated similarly, as were the SMA data sets.

Results

The results are shown in table 6.1. There was a significant difference between the mean r.m.s. of each signal and the mean r.m.s. of the static signal ($p < 0.02$). For all postures on the y- and z- axes the differences were statistically significant at the $\alpha = 0.001$ level. The r.m.s. values were greatest when subjects were standing. The variability was also greatest when subjects were standing.

The r.m.s. was a more sensitive measure than the SMA for determining whether or not the device was being worn. The mean SMA value was significantly different to the mean static SMA value when the subjects were standing ($p < 0.01$), and sitting ($p < 0.001$) but the difference was not significant when the subjects were lying.

Discussion

The r.m.s. data from when the TA device was being worn was significantly different from the data when the TA device was not being worn. The r.m.s. was more sensitive than the SMA in distinguishing between when the device was worn and when the device was not worn. This may be because the r.m.s. treats all three axes separately whereas the SMA combines the three axes and relevant information may be lost in the averaging process.

In this study the distinctions between periods of wearing the device and periods

		static	stand	sit	lie
x-axis	mean	3.93	8.37**	5.78***	4.47*
	std.dev.	0.15	6.59	1.31	1.24
	min	3.66	4.54	3.93	3.79
y-axis	mean	3.73	8.73***	5.02***	4.27***
	std.dev.	0.19	6.80	1.14	0.69
	min	3.30	4.00	3.77	3.58
z-axis	mean	4.11	8.68***	7.03***	6.19***
	std.dev.	0.17	5.38	2.58	1.41
	min	3.85	3.92	3.89	3.74
ρ	mean	6.80	15.19***	10.58***	8.83***
	std.dev.	0.21	10.44	2.4	1.61
	min	6.40	7.67	6.83	6.57
SMA	mean	12.7	21.6**	15.5***	13.2
	std.dev.	0.0169	13.4	3.2	2.1
	min	12.7	11.5	10.3	10.2

Table 6.1: The r.m.s. and SMA values from the filtered signals obtained from 26 subjects standing, sitting and lying, and the values from the static signals obtained when the device was not being worn. Results are given in units of $g \times 10^{-3}$.
* indicates that the value is significantly different to the static value ($p < 0.02$)
** indicates that value is significantly different to the static value ($p < 0.01$)
*** indicates that value is significantly different to the static value ($p < 0.001$)

of not wearing the device were made using data from short periods (20 s) in which the subject remained as motionless as possible. In every day situations the subject would not be expected to remain as motionless as possible, but to move around somewhat more, thereby increasing the r.m.s. values and making the distinction between the two situations simpler. When monitoring free-living subjects heuristic methods can also be introduced to determine whether or not the TA device is being worn. One such method is to measure the time for which the r.m.s. remains at the very low levels expected from an unworn device. The probability that the device is not being worn increases with the amount of time over which there is no movement.

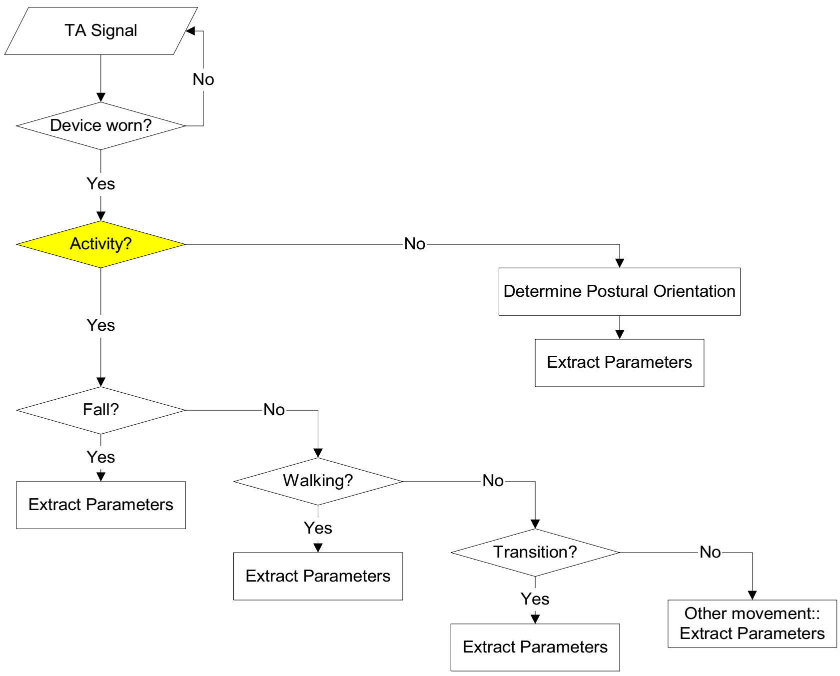
The exception to this is the case in which an adverse event has occurred and the subject remains motionless for an extended period. If, for example, the subject falls and lapses into unconsciousness, she or he would be expected to remain very still. It can be seen from table 6.1 that when the subjects were lying, the minimum r.m.s. value from the worn TA was inside the range of expected r.m.s. values for the unworn TA. In this case it may be difficult to determine whether or not the TA device is being worn if the only consideration is the r.m.s. value of the signal at that time. Other heuristic methods that take into account the movement of the device leading up to the period without motion could be used to deduce whether or not the device is attached to the subject. Alternatively, a user protocol could be established in which the user informs the system whenever the device has been deliberately removed, for example, through placement in a special recharging cradle.

Conclusion

A significant difference was found between the r.m.s. signal value of a worn TA and an unworn TA over a 20 s testing period. The difference in values would be expected to increase over longer periods as people do not normally remain motionless for extended periods. Thus, under normal circumstances, the signal r.m.s. can be used to decide whether or not the TA is being worn at that time.

However, the minimum r.m.s. signal values obtained when the subject was lying were inside the range of signal values expected from an unworn TA. This has implications for occasions in which an adverse event occurs, such as the subject falling unconscious. The signal at this time may be indistinguishable from the signal from an unworn TA if the subject remains motionless for an extended period. Heuristic or procedural methods need to be considered to be certain of whether or not the device is being worn when there is low variability in the signal.

6.5 Classifying Activity and Rest



Classification of activity and rest.

Introduction

If the device is being worn by the subject, data processing and classification can take place. The first component of the classifier system distinguishes between periods of activity and periods of rest. A flowchart of the activity detection algorithm is shown in figure 6.3.

Systems in which accelerometers are placed at a number of locations on the body, typically including the waist and thigh as well as at other locations, have been used to resolve resting states such as sitting, standing and lying, and activities including walking, climbing up and down stairs and cycling [72, 76, 221, 225]. Accelerometry in combination with GPS (global positioning system) [173] has also been used for this purpose. Additionally, single waist mounted units have been used to study gait patterns [70, 193].

Veltink *et al.* [225] and Aminian *et al.* [19] used thresholding techniques to discriminate between activity and rest as part of larger classifiers (refer to section 3.8). These investigators used an approach based on determining whether or not the signal varies with time by comparing a low-pass averaged value of the signal to a preset threshold to test for deviation from the mean. Veltink *et al.* used a low pass filter with a cut-off at 0.1 Hz (after first applying a high pass filter, cutoff 0.5 Hz, and then rectifying the signal), while Aminian *et al.* applied a 10 s averaging window. This approach proved very effective for extended or repetitive activities such as walking or cycling. However, it is limited in that it is insensitive to activities of a short duration, including "transient" movements such as rising from a chair.

In this study an investigation was conducted into an automatic detection system for distinguishing activity from non-activity using only a single waist-mounted triaxial accelerometer (TA). The detection system was designed to be suitable for detection of all significant movements, including repetitive movements such as walking, and "transient" movements such as sit-to-stand transitions.

The detection system compared the time-averaged, integrated signal magnitude to a preset threshold to distinguish between rest and activity. An accurate detection of activity is needed so that the subjects' activities can be further analysed and classified. This requires a high sensitivity. This was determined to be the primary requirement for this detection system.

This method was applied to data collected from 26 normal subjects to distinguish between activity and rest and the system detection performance was evaluated. The system was defined by three parameters; filter length (n), window width (w) and energy threshold (th). The effects of these were explored for a wide range of values

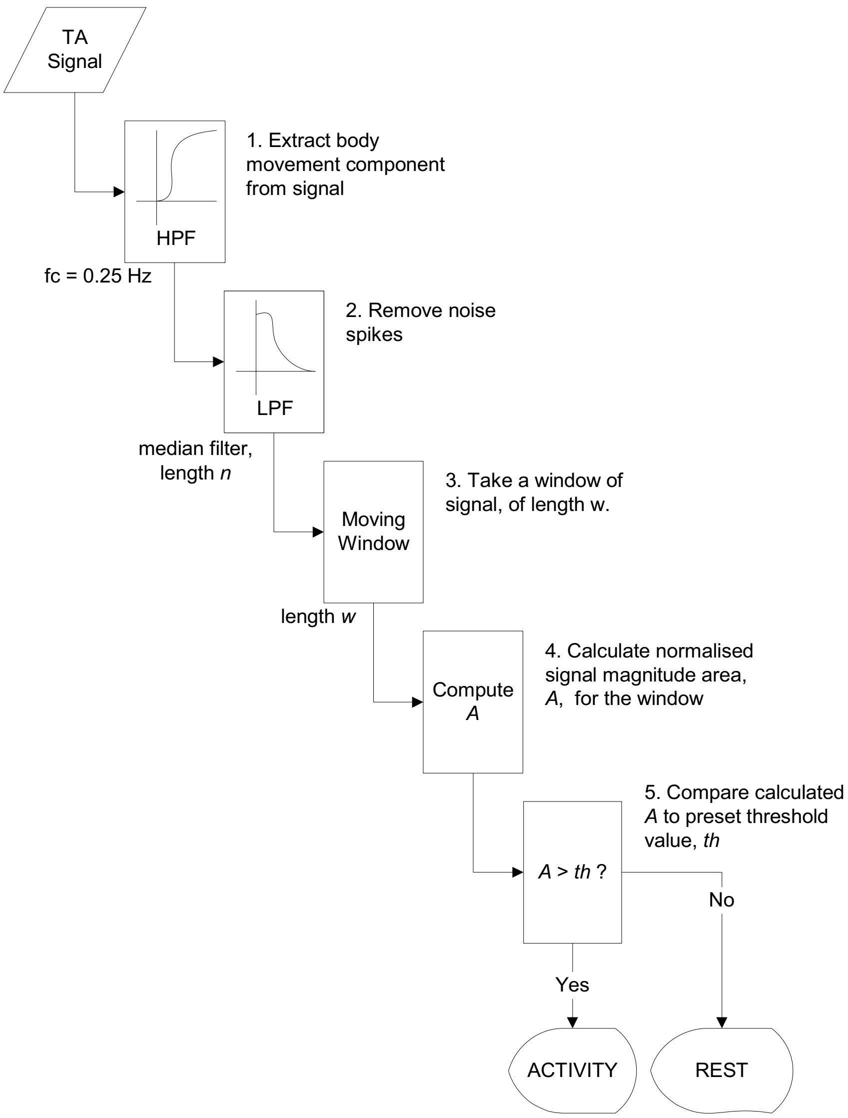


Figure 6.3: Flowchart of the activity detection classifier

and optimal ranges were determined for the subject cohort.

Experimental Procedure

An experiment was conducted in which 26 healthy volunteers with no mobility limitations (7 female, 19 male; age 30.5 years ± 6.3 years standard deviation) performed a sequence of normal daily movements in a controlled laboratory setting while wearing the TA. The testing procedure was the same for all subjects. The subject was told to attach the TA at the waist, above the right anterior superior iliac spine, as this was identified as the preferred site by the subjects. Each subject carried out 11 distinct activities, being sit-to-stand transitions, stand-to-sit transitions and walking. These were interspersed by 12 distinct rest periods of either standing or sitting. The sequence was: (i) stand (30 s); (ii) sit down into a lounge chair; (iii) remain sitting (30 s); (iv) stand up; (v) remain standing (10 s); (vi) walk along a flat, straight corridor; (vii) remain standing (10 s); (viii) sit down into an office chair; (ix) remain sitting (30 s); (x) stand up; (xi) remain standing (10 s); (xii) walk up and down a flight of stairs; (xiii) remain standing (10 s); (xiv) sit down into an office chair; (xv) remain sitting (30 s); (xvi) stand up; (xvii) remain standing (10 s); (xiii) walk along a flat, straight corridor; (xix) remain standing (10 s); (xx) sit down into a lounge chair; (xxi) remain sitting (30 s); (xxii) stand up; (xxiii) remain standing (10 s). The protocol took eight minutes to complete. The subject was directed through the procedure by an investigator who identified the time of onset and offset of each segment using a stopwatch. The investigator indicated to the subject what movement to make and when to carry it out. Every data sample was time stamped by the data acquisition system so that each activity could be identified on the resultant signal trace, using the independent timing data obtained by the investigator. Figure 6.4 shows a typical sample of data.

Thirteen of the subjects were randomly selected as a control group, and the other thirteen were allocated to a test group (Control group: 4 female, 9 male; age 30.9 years ± 9.0 years standard deviation; Test group: 3 female, 10 male; age 30.5 years ± 6.4 years standard deviation). The TA signals from the control group were used to identify optimal sets of parameters for the detection system, which was then applied to the test group and its performance was evaluated.

Data Analysis

Activity acceleration amplitude and duration are highly variable; between different activities, between subjects and even for the same subject and activity. For example,

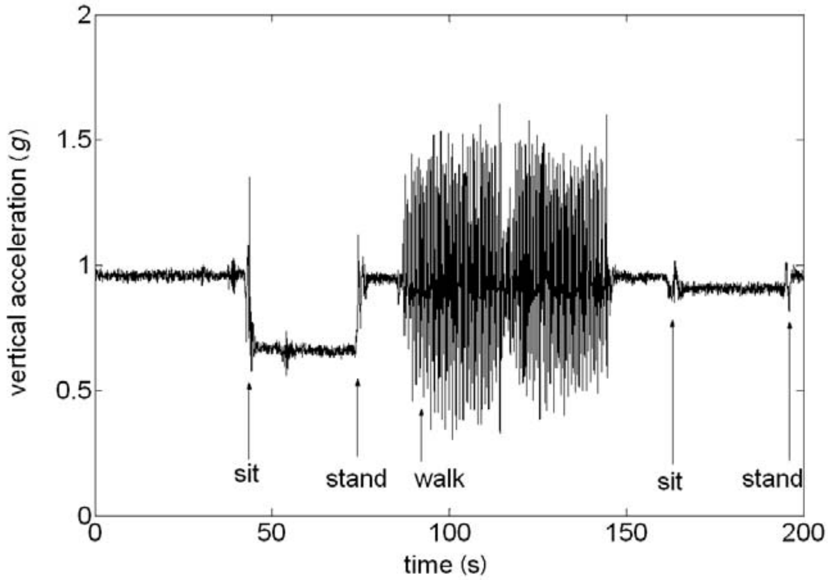


Figure 6.4: A typical sample of data collected showing the vertical axis acceleration ($g = 9.81\,\mathrm{m.\,s^{-2}}$) from a subject performing part of the test sequence. The activity segments were timed by an investigator and correlated with the time stamp of the signal. The different activities are indicated.

a sit-to-stand transition may take from 1 s to more than 3 s in healthy subjects [122], and even longer in frail elderly or disabled subjects [172]. If, for example, a subject sits rapidly into a chair, a large signal magnitude over a short duration is seen, in contrast to a slow movement, in which a smaller signal magnitude over a longer period is observed, as shown in Figure 6.5. Thus, in order to identify activity, both the magnitude and duration of the signal need to be taken into account.

One way of including both effects is to calculate the signal's magnitude-area ($magnitude \times time$) and compare it to a preset threshold. Bouten *et al.* [31] found that, after removing the gravitational components of the signals by high-pass filtering the signals, the sum of the integral of the signal magnitudes from a TA is proportional to metabolic energy expenditure in the activities of daily living with correlation coefficient, $r = 0.89$ (refer section 3.7). The normalised signal magnitude area (A), defined in equation 5.20, was used as the basis for identifying periods of activity in this study.

The signals obtained from the TA were processed in the following way. Each of the three orthogonal signals from the TA was passed through a high pass filter (finite impulse response filter with cut-off frequency at 0.25 Hz) to remove the gravitational acceleration component from the signal.

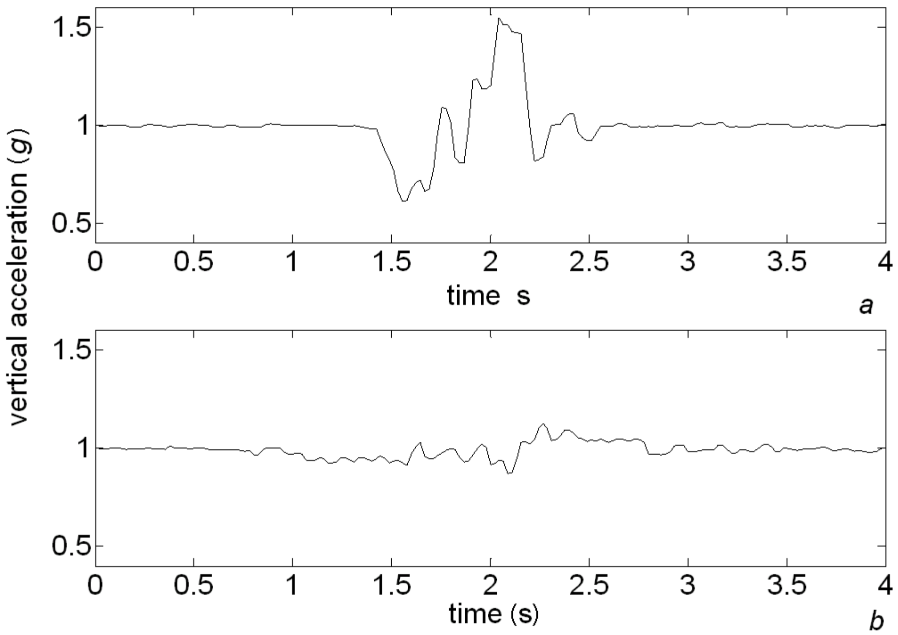


Figure 6.5: A comparison between the data for two stand-to-sit transitions, showing the vertical axis acceleration ($g = 9.81\,\mathrm{m.\,s^{-2}}$) versus time. (a) shows a typical rapid transition, of the order of 1 s in duration. (b) shows a typical slower transition of the order of 2.5 s in duration. Note that the magnitude of the acceleration in the rapid transition is approximately 5 times larger than that in the slow transition.

Each signal was then passed through a median (nonlinear low pass) filter of length n samples to remove high frequency noise spikes. A non-overlapping averaging moving window, of width w seconds, was applied to the signal, and A calculated for each window. A was then compared to a fixed preset threshold, th, to determine the presence or absence of activity in the signal at a given time. th was a measure of the SMA, having units of ms^{-2} and, like A, was independent of the window width. The threshold comparison, $A > th$, was used to identify activity in the signal. Contiguous windows containing activity were joined together to form periods of activity interspersed by periods of rest. These periods of activity were compared to the periods of actual activity in the following way. If a group of contiguous, joined windows that contained the time at which an activity occurred was classified as containing activity, then this was recorded as a true positive. If a group of contiguous, joined windows that did not contain the time at which an activity occurred had been classified as containing activity, then this was recorded as a false positive. Negatives were defined similarly. In this process, a definitive recording of the start and endpoints of the activity was not sought, but rather that an activity had been detected within a block of time.

The effects of three parameters affecting the system's function were investigated. These were (i) the length of the median filter, n, (ii) the width of the window, w, and (iii) the threshold value, th. Each parameter was varied from its minimum value to a value above which discrimination between rest and activity did not occur.

First of all, the effect that the parameters n, w, and th had on the detection system was investigated, using the TA signals from all 26 subjects. Then, as a second task, 13 of the subjects were randomly selected as a control group as outlined above. The rates of true and false positives were measured using each combination of these three parameters. The sets of parameters were ranked in descending order of true positive rate (sensitivity) and within this ordering, in increasing order of false positive rate (1 - specificity). This allowed the optimal set of parameters to be determined.

As discussed earlier, given the criterion that a high sensitivity was more important than a high specificity, acceptable parameter sets were defined as those that gave specificities above 0.9, and sensitivities as high as possible, but not below 0.9.

The system, using the optimal parameters as determined for the control group, was tested on the remaining 13 test group subjects, and the effectiveness of the system was evaluated for the test group in terms of sensitivity and specificity.

Results

Filter lengths $n = 3, 5, 7, \ldots, 89$ samples, window widths $w = 0.2, 0.4, 0.6, \ldots, 4.0\,\mathrm{s}$, and thresholds $th = 0, 0.0225\ g, 0.0450\ g, \ldots, 0.9000\ g$ were tested. The effects of the parameters n, w, and th on the detection system were investigated, using data from all 26 subjects. Each of the three parameters was found to affect the specificity and the sensitivity of the system.

The sensitivity of the system was found to be controlled by a relationship between the product of n and w, and threshold, th and by a subsequent relationship between n and w. Figure 6.6 shows the relationship between $n.w$ and th and the effect on the discrimination ability of the system for all 26 subjects. Sets of parameters that achieved both sensitivity and specificity greater than 0.9 are shown. Curves of best fit (3rd degree polynomials) through the upper and lower limits are also shown. The relationship between n, w and the discrimination ability of the system is illustrated in figure 6.7 for the instance where $th = 0.1575\ g$.

The effect of the filter length, n, on the windowed signal magnitude area, A, was found to have two components. The first component acted on the measurement for the individual subject, and is illustrated in figure 6.8a. As n was increased, the difference between A for activity and rest for any one subject was reduced, making discrimination more difficult. The second component acted across subjects, and is shown in figure 6.8b. As n was increased, the differences between subjects decreased, making detection easier until the first effect became too significant.

In the second task, optimal parameters were found for the control group and then applied to the test group to determine their effectiveness. Figure 6.9a shows a receiver operating characteristic (R.O.C.) curve (true positive rate versus false positive rate) for all of the parameters tested on the subject control group. Figure 6.9b shows the R.O.C. curve with the parameters that, on the control group achieved a sensitivity and specificity greater than 0.9. The sensitivity and specificity achieved when these same sets of parameters were applied to the test group are superimposed on the diagram.

Table 6.2 lists the proportion of parameters tested on the control group that achieved various true positive rates and a false positive rate less than 0.1. Eleven parameter combinations yielded the same optimal result. These are listed in Table 6.3, together with their sensitivities and specificities when applied to each of the control and the test groups. When each of the 11 sets of optimal parameters from the control group were applied to the test group, the true positive rate of the system ranged from 0.98 to 0.99 and the false positive rate ranged from 0.12 to 0.06.

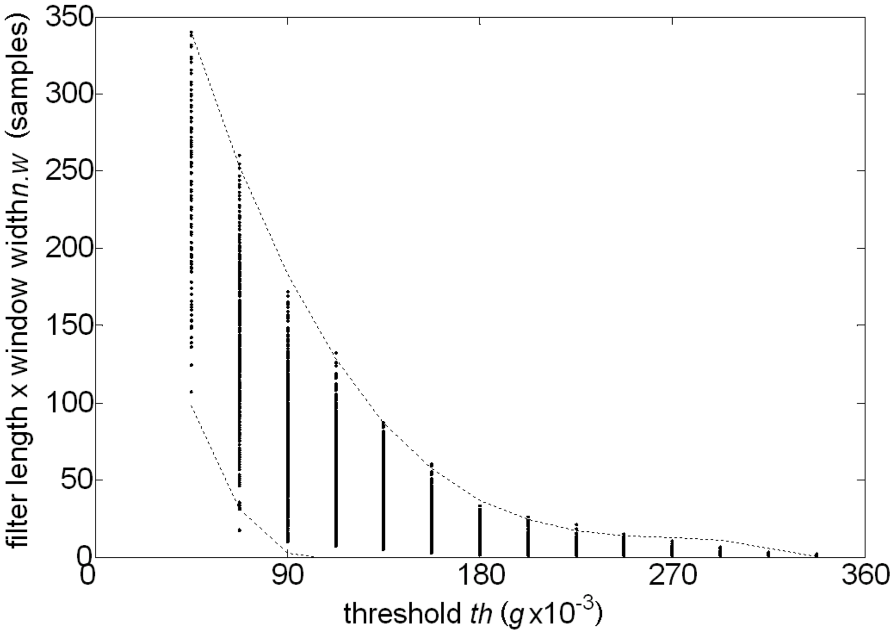


Figure 6.6: Filter length (n) $\times$ window width (w) versus threshold (th), plotted for all sets of parameters giving both sensitivity and specificity greater than 0.9, across all 26 subjects. Note that, for these parameter sets, $n.w$ is bounded by smoothly decreasing functions of th.

True positive rate greater than, or equal to	**Percentage of sets of parameters**
0.90	5.58
0.95	4.04
0.99	1.56
1.00	0.80

Table 6.2: Proportion of sets of parameters that gave a false positive rate less than 0.1 in the control group ($N = 13$) as a function of true positive rate.

			RESULTS ON CONTROL SET		RESULTS ON TEST SET	
n (samples)	w (s)	th (g)	true positive rate	false positive rate	true positive rate	false positive rate
13	0.8	0.1575	1	0.04	0.99	0.06
15	0.8	0.1575	1	0.04	0.99	0.06
17	0.8	0.1575	1	0.04	0.98	0.08
17	1.4	0.135	1	0.04	0.99	0.12
19	0.8	0.135	1	0.04	0.99	0.08
19	1.4	0.135	1	0.04	0.99	0.08
21	0.8	0.135	1	0.04	0.98	0.12
23	0.8	0.135	1	0.04	0.99	0.08
25	0.8	0.135	1	0.04	0.99	0.10
27	0.8	0.135	1	0.04	0.99	0.12
29	0.8	0.135	1	0.04	0.99	0.08

Table 6.3: Optimal parameters for activity identification in the control set ($N = 13$). The true and false positive rates achieved for this set of parameters on the control set was optimal, being 1.00 and 0.04 respectively. The false positive rate of 0.04 in the control set results corresponds, in each instance, to the same two rest periods being incorrectly categorised as activity. In the first instance, a subject was fidgeting while standing, in the second instance a subject, while sitting, shifted in the seat. The results achieved when these sets of parameters were applied to the test set ($N = 13$) are also given.

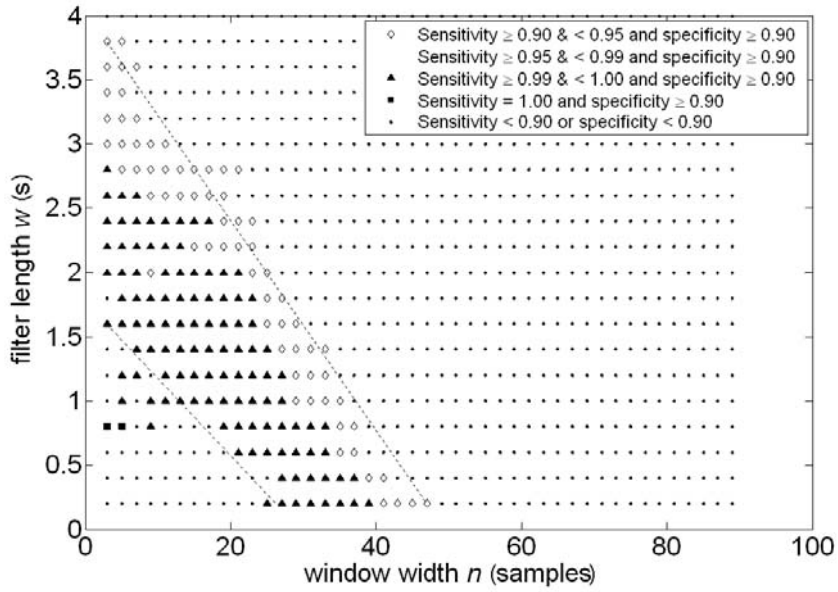


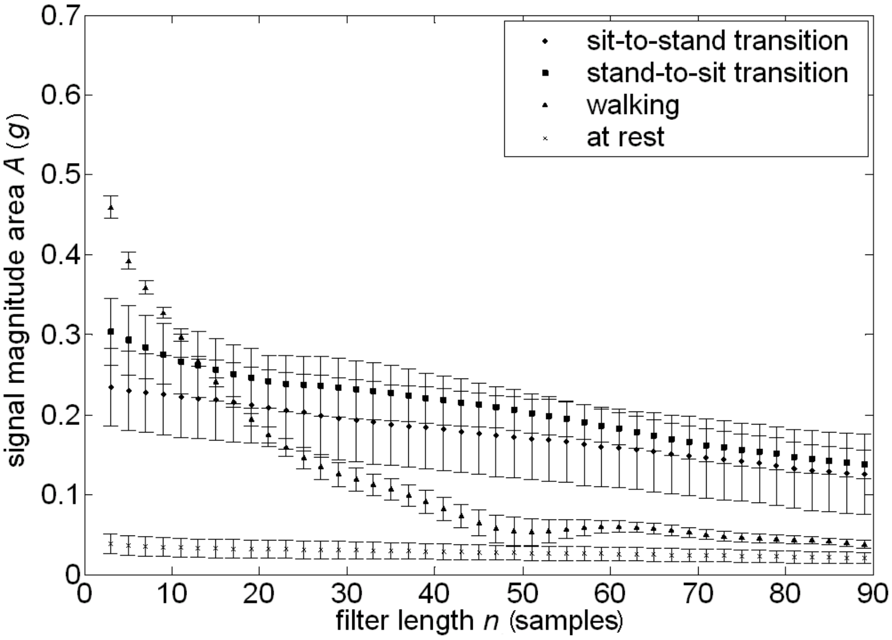
Figure 6.7: Window width (w) versus filter length (n) across all 26 subjects. All sets of tested n and w where threshold $th = 157.5 \times 10^{-3}\ g$ are plotted. Bands of sensitivity, with specificity greater than 0.9, are shown. The linear bounds on the band, specificity greater than 0.9, are indicated by dotted lines.

Discussion

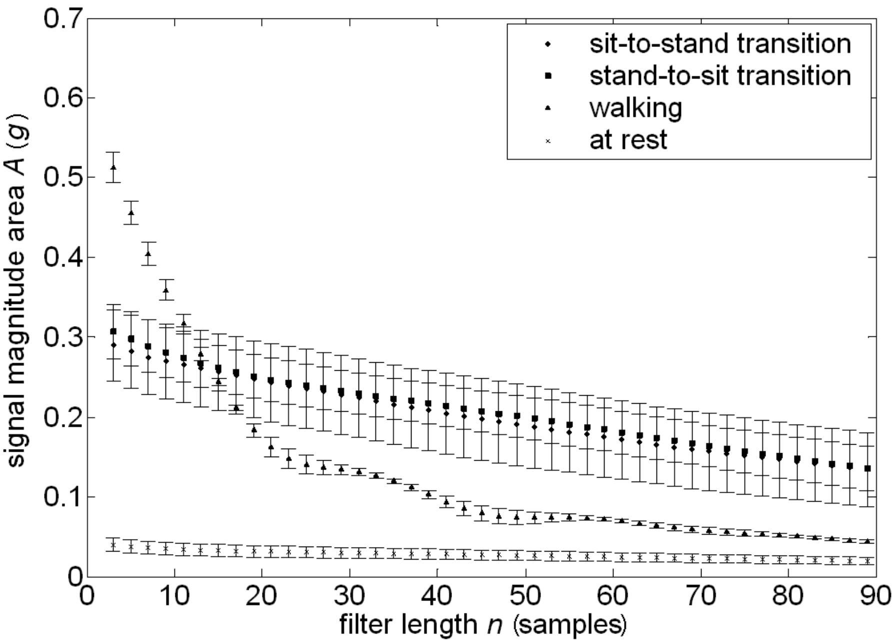
It is important to be able to detect movements such as walking and postural transitions because they provide valuable information on the functional status of the patient. On the other hand, it is not necessary to identify small movements such as a slight readjustment of posture while sitting. There is always some movement when at rest (sitting, standing or lying) and the aim of this investigation was to find a robust method for consistently distinguishing between significant activity and resting states.

The normalised signal magnitude area, A, is a parameter that can be quickly and easily calculated from the incoming signal. This allows the algorithm to be used in a "real-time" context. This parameter also has the useful property that it is an estimator of the metabolic energy expenditure, and can also be used for longitudinal tracking of physical activity levels.

Sets of parameters that resulted in accurate discrimination showed a relationship between th and the product of w and n, and a relationship between n and w. When the data from all 26 subjects were analysed, all of the parameters with high sensitivity and specificity were contained within a band on a plot of $n.w$ against

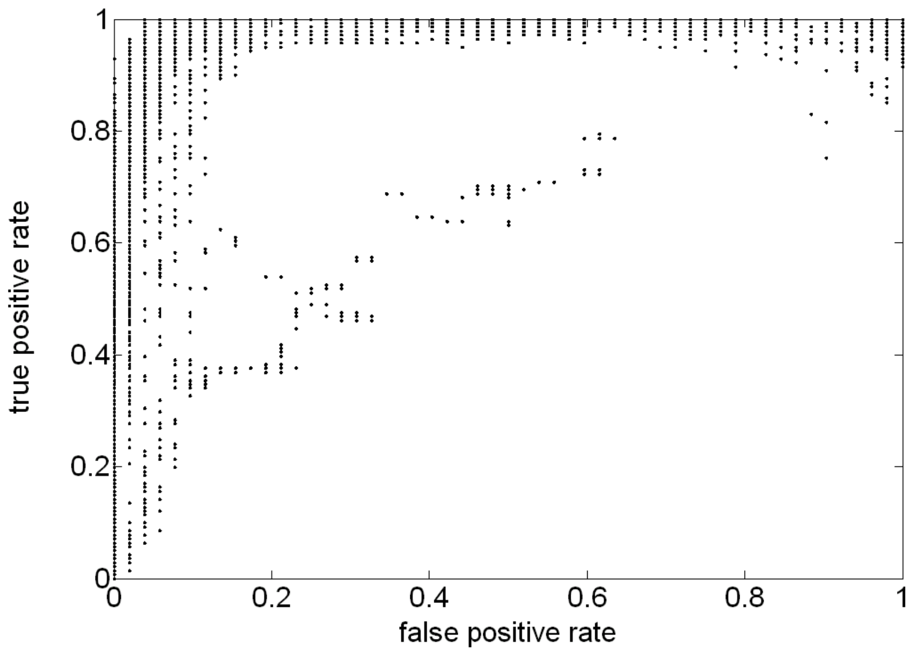


(a)

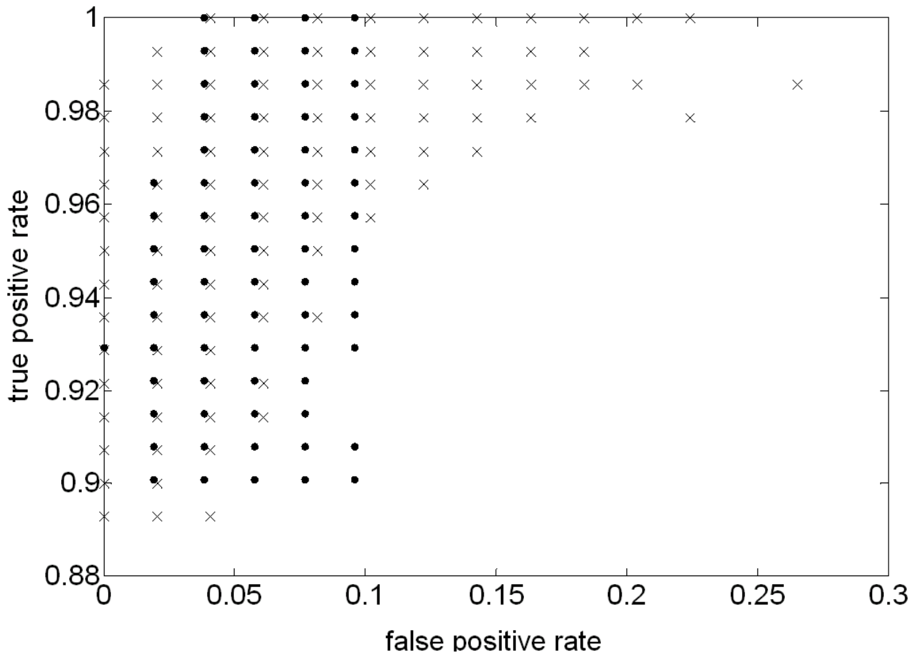


(b)

Figure 6.8: The effect of filter length, n, on the signal magnitude area, A, when window width, $w = 0.8\,\mathrm{s}$. (a) An example of data for one subject. As n increases, activity segments more closely resemble non-activity. The points indicate the mean A as a function of n for each of the identified activities for one subject. The error bars represent the standard deviation of these activities for this subject. (b) For all 26 subjects. As n increases, the differences between subjects decreases, making the overall classification better. Concurrently, however, the differences between activity and non-activity are also decreasing. The points indicate the mean A as a function of n for each of the identified activities for all subjects. The error bars represent the standard deviation over all subjects.



(a)



(b)

Figure 6.9: (a) Receiver Operating Characteristic (R.O.C.) curve for the combinations of parameters investigated, applied to the subject control group ($N = 13$). Each point represents a different combination of filter length (n), window width (w) and threshold (th). Note that there were multiple combinations of the parameters achieving the same sensitivity and specificity. The optimal parameters are those located at the top left hand corner of the curve. (b) Detail of the R.O.C. for the combinations of parameters that gave sensitivity and specificity better than 0.9 in the control group ($\cdot$) together with the results of these same parameter sets when applied to the test group (x).

th (figure 6.6). The band was described above and below by smoothly decreasing curves. However, not all sets of parameters inside this band yield good discrimination results. A second condition described a relationship between n and w. For each th and sensitivity, the range of w was linearly bounded above and below as shown in figure 6.7.

The data for this study alternates periods of rest with periods of activity. When the system is working optimally, it should detect a period of rest followed by a period of activity, followed by another period of rest, and so on. If the system is insufficiently sensitive, periods of activity are not detected, resulting in a rest-activity-rest sequence in the signal being classified as rest. If the system is completely insensitive, as occurs when the energy threshold, th, is set too high, the entire signal is classified as a single rest period. If the system is too sensitive then parts of rest periods are classified as activity. In the extreme case, the entire signal is classified as a single period of activity. The result of either error (oversensitive or insensitive) is to reduce the ability of the system to discriminate between rest and activity. Thus, the energy threshold parameter, th, needs to be carefully chosen to provide a balance between sensitivity and specificity.

The median filter, which was applied to the signal in order to filter out noise, affects the energy contained in the signal. The longer the filter length, n, was made, the smoother the signal became and the more energy was lost from the signal. Increasing the filter length made the signal in the activity periods become more like the signal in the rest periods for each subject and this made the distinction between activity and rest more difficult (figure 6.8a). However, as n was increased further, the accuracy of the system improved. This was due to a second effect: the heavier smoothing made the activity periods more uniform across the different subjects, thus making it easier to distinguish between periods of activity and rest across multiple subjects (figure 6.8b). This effect peaked at around $n = 19$ samples. As n was increased still further, the accuracy of the system decreased as the ability to distinguish between activity and rest was lost.

Ideally, the window width, w, would be exactly matched to the width of the activity being assessed. The timescale of human movements range from basic reaction times of 160–190 ms to simple movements (such as sit-to-stand transitions) that take around 1–3 s [233]. Extended movements, such as walking, can occur over indefinite periods.

The variability in activity duration meant that it was not possible to find a window width, w, that was matched to the width of all activities. If w was substantially longer than the length of an activity, the window area contained more signal from the adjacent resting periods than from the activity. When the energy was averaged over the whole window, the result was not distinguishable from a window containing only a resting period. Using shorter windows, or overlapping windows, increased the proportion of window that was filled with activity, and hence increased the detection rates for the same threshold value. However, if the window width was too short, the system became more susceptible to false positives as brief transients in the resting signal became interpreted as movement. Using a window width that was shorter than the shortest expected activity meant that at least half of the window contained dynamic activity when the window was placed over an activity and so increased the likelihood of it being detected as activity.

The best values for the window width, w, were found to be around 1 s (0.8–1.4 s) for this data set. The optimum value for w found in this investigation is consistent with both the timescale of human movement, and the duration of the fastest activity measured in our sequence.

The TA signals are a linear combination of the gravitational acceleration component signal and the body movement component signal. The main limitation of this method occurs in the need to separate the two. This is usually done using a high pass (or a low pass) filter, with the low pass component being regarded as the gravitational component and the high pass component being regarded as the body movement component [31, 72, 226]. However, the two component signals have a frequency overlap. The gravitational component measured by each axis of the TA changes with the postural orientation of the subject, and the body movement ranges from 0 Hz, when there is no movement whatsoever, up to several hertz. This frequency overlap means that perfect separation between the two components cannot be achieved by filtering. However, in this study, it was found that using a high pass filter with cut-off of 0.25 Hz to separate the gravitational and body-movement accelerations allowed periods of rest and activity to be distinguished.

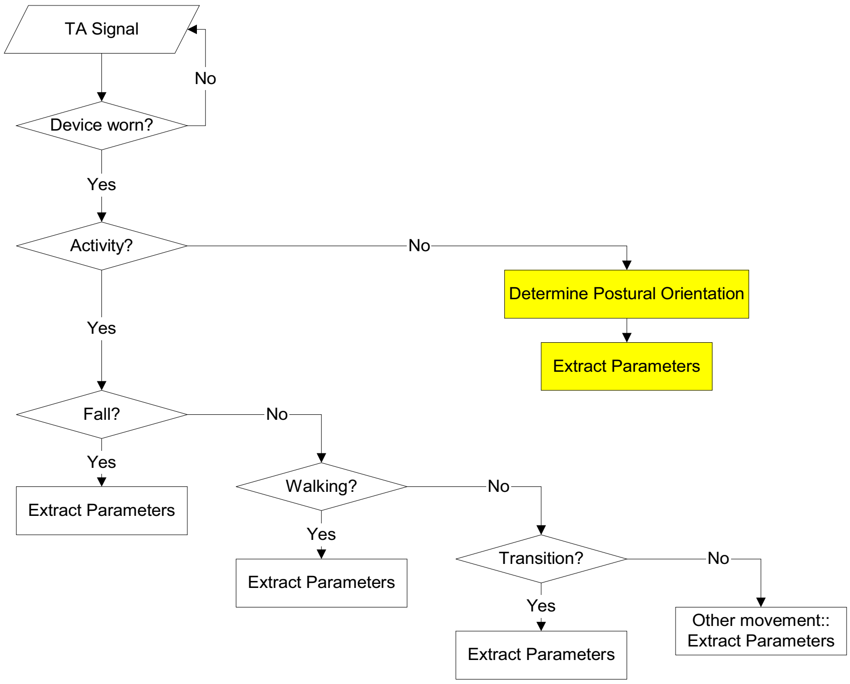
The optimal values of n, w, and th identified by the algorithm are influenced to some extent by the 0.25 Hz cut-off separation filter, but good discrimination results were still achieved. It would be anticipated that similar, but not identical, results would be achieved using a different separation filter.

It seems likely that this method would still be effective in detecting periods of activity, that the same relationships between parameters would hold, and that similar parameter values would be appropriate, although the optimal parameters would be expected to change as a function of subject cohort, and possibly also as a function of the separation filter. For example, frail, ill or housebound patients are likely to move more slowly and generate lower accelerations, and so a lower valued n and a longer w may perform more effectively on such a cohort. This was investigated in a later study with elderly subjects (refer to section 7.8).

Conclusion

This study has shown that it is possible to distinguish between activity and resting states using a single waist-mounted triaxial accelerometer by means of a mean acceleration thresholding approach. A median (low pass) filter was applied to the signal to remove noise spikes; then analysed the signal on a window-by-window basis, comparing the mean acceleration contained in the windowed signal to a predetermined threshold. It was found that the relationship between the product of the filter length and the window width, and the threshold value was most important in determining sets of parameters that would perform to the required specifications. The sets of parameters that yielded a sensitivity of 1 and a specificity greater than 0.96 when applied to data from a control group of 13 subjects were applied to data from a test group of subjects, and resulted in a sensitivity greater than 0.98 and a specificity between 0.88 and 0.94. This shows the robustness of the technique for separation of activities from rest, in the case of controlled movements.

6.6 Classifying Rest



Classification of resting postures.

6.6.1 Introduction

The second component of the classifier is the set of algorithms to determine the postural orientation of the subject during periods of rest.

Systems in which accelerometers are placed at a number of locations on the body, in particular on the trunk and the thigh, have been used to classify resting state data into sitting, standing and lying [19, 72, 76, 221, 225]. In this study an algorithm is developed to classify postural orientation during rest into sitting, standing and four subpostures of lying using only a single waist-mounted TA.

The postural orientation can be classed as upright or lying. If the subject is upright then the orientation can be classified as either standing or sitting. If the subject is lying, then the lying orientation can be sub-classified depending on which way the subject is lying. Once a period of rest has been classified then relevant parameters can be extracted. Figure 6.10 shows an overview of the resting state classifier algorithms.

Much of the resting state classification can be achieved deterministically using the model and methodology developed in section 5.4.3.

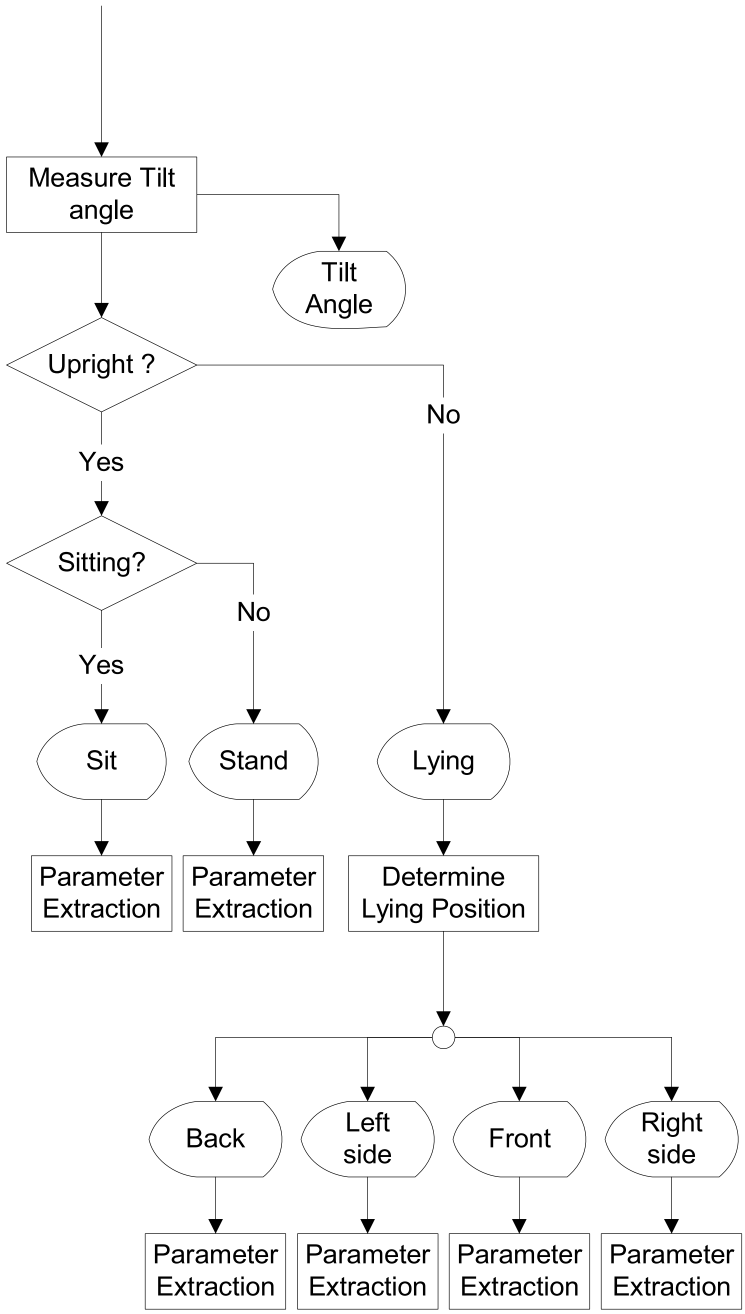
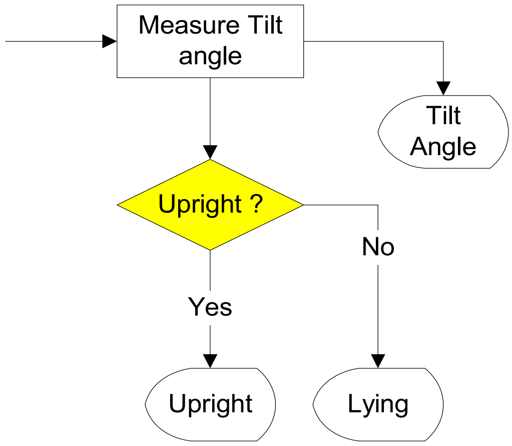


Figure 6.10: Flowchart of the resting state classifier

6.6.2 Classifying Upright and Lying



Classification of upright and lying postures.

Introduction

Upright and lying pertain to the tilt angle of the subject. The tilt angle, ϕ, was defined to be the angle between the vertical axis of the TA and the gravitational vector (illustrated in figure 5.5). As the TA was placed so that its vertical axis was aligned with the vertical axis of the subject, ϕ was also a measure of the tilt angle of the subject.

When the subject was standing, sitting upright, or lying down the distinction between upright and lying was clear cut. This is evident from figure 5.25, which shows that there was no overlap in the TA z-axis values, from which ϕ is derived, between standing and lying states. Thus, perfect discrimination was possible in these cases.

The distinction becomes less obvious when the subject is reclining, on a couch, or sitting up in bed. In these cases the subject is halfway between sitting upright and lying and it is unclear what classification should be made. Here, a measure of the tilt angle can be more useful than a dichotomous classification. The decision was made to limit the lying classification to postural orientations that were close to horizontal lying, and to classify other reclining states as upright. These could then be subclassified as sitting (reclining) and the tilt angle recorded as a state parameter.

Experimental Procedure

Two data sets were used to investigate the effect of applying this algorithm to the signals from a TA placed above the right anterior superior iliac spine. Data from 23 normal subjects lying supine, on the left and right sides and face-down were collected using the procedure described in section 5.4.3. Data from 26 normal subjects when standing, sitting in an office chair, sitting in a lounge chair and sitting in an office chair, leaning forwards over a keyboard were collected using the procedure described in section 6.5.

Data Analysis

The TA signals from each postural orientation were averaged over the period that the subject was in that position. This process yielded a 3-vector representing the TA output for each subject in each position.

An algorithm to achieve discrimination between upright and lying states was developed. This algorithm compared the tilt angle to a fixed threshold of 60° and classified the postural orientation based on the result. A tilt angle of 60° corresponded to a z-axis reading of 0.5. If $z > 0.5$ then the subject is classified as upright. If $-0.5 < z < 0.5$ then the subject was classified as lying. If $z < -0.5$ then the subject was upside down!

Results

Figure 6.11 shows mean vertical axis data taken from 23 normal subjects. These data were collected during the study described in section 5.4.3. The dashed line indicates $z = 0.5$. All of the upright states were completely contained above the line while all of the lying states were completely contained below the line. Thus, classifications were made with 100% accuracy.

Discussion and Conclusion

This simple algorithm distinguished between upright and lying states with 100% accuracy. This result was not unexpected since the underlying premise was that the subject moves from a vertical position to a horizontal position when moving from upright to lying, which for cases of standing, sitting upright, and lying down, is true. This algorithm was later tested on data from unsupervised subjects performing a sequence of known activities (chapter 7).

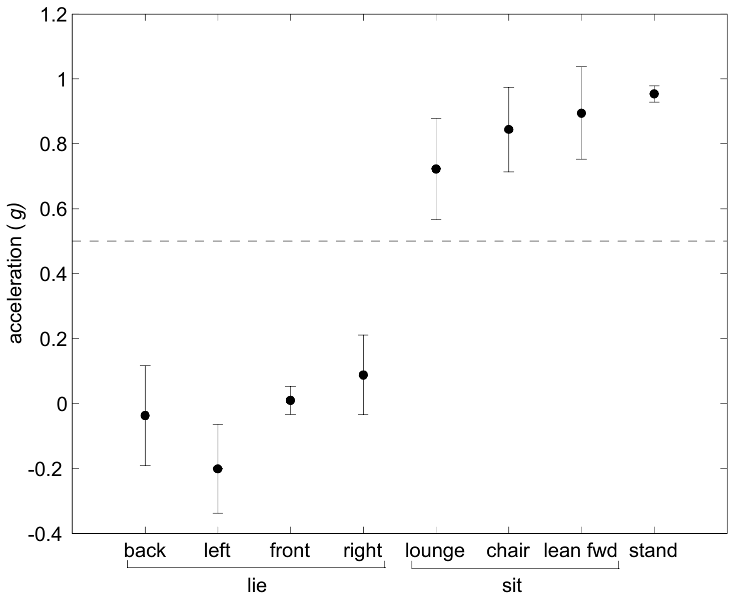
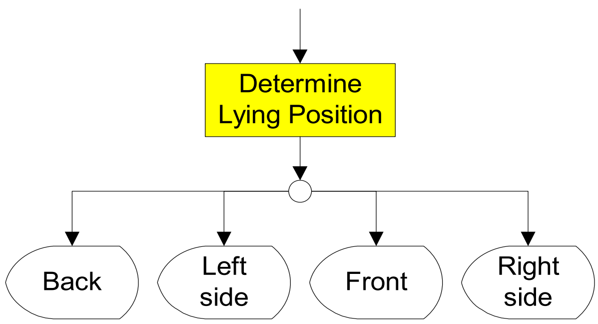


Figure 6.11: Mean TA vertical axis output signals for 8 different postural orientations when the device was placed above the right hip ($N = 23$). Error bars represent 1 standard deviation. The dotted line is the threshold value of 0.5. There was complete discrimination between the upright and the lying states.

6.6.3 Classifying Lying Subpostures



Classification of lying postures

Introduction

The lying subclassification algorithm was developed as an extension of the postural orientation modelling that was described in section 5.4.3. The purpose of the algorithm was to discriminate between the four lying subpostures of lying supine, lying face down, lying on the left side, and lying on the right side. Such information can be used to provide more information on the subject's bed rest habits [76]. It may also provide useful information in the event of a fall.

Experimental Procedure

Twenty-three normal subjects participated in the study. The subject cohort was the same one that was used in the study described in section 5.4.3 (7 female, 16 male; age 30.5 ± 6.3 years standard deviation). The TA was attached at the front-right of the waist above the anterior superior iliac spine. Data were collected from the subject in eight postural orientations: (i) standing; (ii) lying on the back; (iii) lying on the left side; (iv) lying on the front; (v) lying on the right side; (vi) sitting on a lounge chair; (vii) sitting on an office chair; and (viii) sitting on an office chair, leaning forward over a keyboard. Subjects remained in each position for twenty seconds.

Data Analysis

The raw signals from the TA were low pass filtered (3 dB point 0.25 Hz) to retain only the gravitational component of the signal. The low-pass filtered signals were analysed on a second-by-second basis. Each second of data was averaged to produce a position vector. This vector was processed using each of the models (discussed below) and the postural orientation of the subject was classified. Thus, 20 classifications were made for each 20 second data sample.

The regular and elliptical cylinder models from section 5.4.3 were used to classify the postural orientation of the subject. The rectangular model was also applied for purposes of comparison. Each postural orientation was classified as one of (i) upright; (ii) lying supine; (iii) lying right side down; (iv) lying face down; or (v) lying left side down.

The results of the study in section 5.4.3 were used to compute predicted signal vectors for standing upright and lying supine from each of the three models. The predicted signal vectors for lying right side down, lying face down and lying left side down were calculated by rotating the predicted vector for lying supine about the z-axis by 90°, 180° and 270° respectively. Each model was tested using (i) the nominal angles of placement, t_{nom} (rectangular model: $t_{nom} = 180°$, cylinders: $t_{nom} = 225°$), and (ii) the mean optimal angles of placement, t_{mean}, as determined from the earlier model evaluation (rectangular model: $t_{mean} = 180°$, elliptical cylinder: $t_{mean} = 219°$, regular cylinder: $t_{mean} = 213°$).

Classification was achieved by comparing the measured vector to each of the vectors predicted by the model and selecting the nearest (in an l_2 sense) vector to the measured vector. The predicted values for the four lying postures are evenly distributed on a circle in the x–y plane (figure 6.12). The plane can be divided into

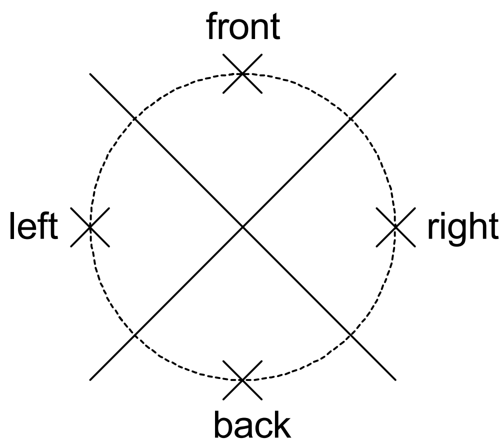


Figure 6.12: The predicted values for the four lying postures are evenly distributed on a circle in the x–y plane. The plane is divided into four quadrants and actual lying postures are classified according to the quadrant that the mean acceleration vector lies within, when projected onto the x–y plane.

four quadrants, each one representing one of the four postural subclassifications. Each postural subclassification was then tested simply by establishing whether or not the projection of the measured acceleration vector onto the x–y plane lay in the quadrant pertaining to that classification (figure 6.13).

In order to evaluate the classification a scoring system was applied. Classification of each 20 s postural orientation sample was either (i) fully correct; (ii) partially correct; or (iii) not correct. If the whole 20 s of one postural orientation sample was correctly classified, then it was given a score of 1. If none of the sample was correctly classified then it was given a score of 0. If part of the sample was correctly classified and part misclassified then it was give a score of 0.5, irrespective of how many parts of the sample were incorrectly classified. The classification accuracy of a model was given by the sum of the scores divided by the total number of samples. When comparing classification accuracy between the models, a Kruskal-Wallis statistical test was used.

Results

Table 6.4 summarises the classification results from the models. In the sub-classification of lying states, the cylindrical models were $98 - 99\%$ accurate but the rectangular prism model performed poorly with only 65% accuracy.

There was no significant difference between the classification accuracy of the elliptical cylinder and the regular cylinder, nor was there any significant difference

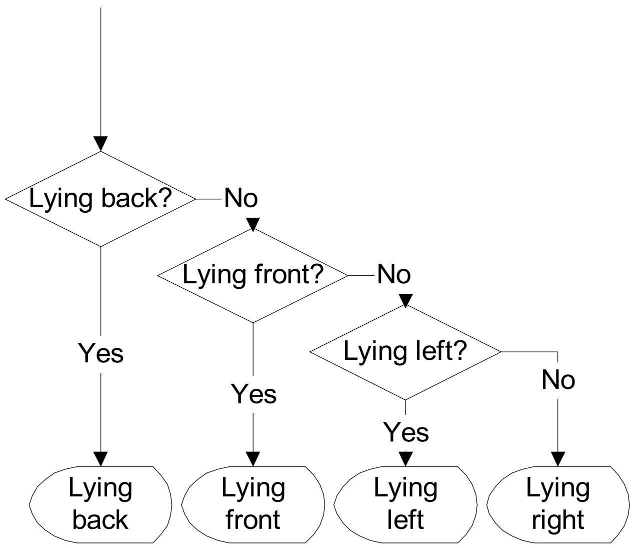


Figure 6.13: Classification of lying postures.

	N	correct	part correct	% correct
Rectangular prism	92	50	20	65.2
Elliptical cylinder with t_{mean}	92	89	3	98.4
Elliptical cylinder with t_{nom}	92	91	0	98.9
Regular cylinder with t_{mean}	92	91	0	98.9
Regular cylinder with t_{nom}	92	91	1	99.5

Table 6.4: A comparison of the prismatic models in classifying lying subpostures. N represents the number of 20 second samples. "Part correct" indicates that different sample sections were given different classifications by the model, and some of the classifications were correct. These samples were designated as "part correct" and given a weight of 0.5 (rather than 0 for incorrect or 1.0 for fully correct) in order to determine the overall accuracy of the system.

in classification accuracy in either model when t_{nom} were used rather than t_{mean} ($p = 0.574$). When t_{mean} were used, the regular cylinder model classified one subject as lying on the front when the actual orientation was lying on the right side, but all other postural orientations were correctly identified. The elliptical cylindrical model produced almost identical results, but here a different subject was classified as lying on the right side for several seconds while actually lying supine, and two other subjects were classified as lying front for part of the time that they were lying on their right sides. When t_{nom} were used, the regular cylinder model classified one subject as lying on the right side for part of the time when the actual orientation was lying on the front, but all other postural orientations were correctly identified. The elliptical cylindrical model classified all but one sample correctly; here a subject was classified as lying on the front when the actual orientation was lying on the right side.

Discussion

The algorithm developed in this study categorised the lying state into four sub-postures with a high degree of accuracy when a cylindrical model of the subject was used. The finding that the cylindrical models allowed postural orientations to be successfully classified is in agreement with work of other researchers. Aminian *et al.* [19] used a symmetrically placed trunk-mounted accelerometer and assumed that when the subject was standing the whole of the gravitational acceleration was along the vertical axis, and when the subject was lying it was distributed across the other two axes, with no component on the vertical axis. This led to successful classification of postural orientation. Veltink *et al.* [225] used a similar approach to data from a tangential thigh accelerometer, a radial trunk accelerometer and a trunk accelerometer perpendicular to the sagittal plane to successfully distinguish between standing, sitting, and the four different lying subpositions.

The modelling study of section 5.4.3 found that the elliptical cylinder more accurately reflected the figure of the subject than did the regular cylinder. This was not reflected in the classification accuracies of the two models, which were indistinguishable. Similarly, although use of t_{mean} provided more accurate modelling than use of t_{nom} there was no difference in the classification accuracies of the two. This may have been due to the high classification rates which meant that a small change in the model accuracy makes little difference to the final outcome. These results also indicate that the classification algorithm is tolerant to some inaccuracy in the reference model.

Given that the two cylindrical models performed equally well, the regular cylinder model was chosen for use in future work. The reason for this was that the regular cylinder is a simpler model than the elliptical cylinder as it has no subject dependent parameters. (In fact, the two models are topologically equivalent. The difference is that in the elliptical cylinder the dimensions of the ellipse are varied in order to reflect the shape of the individual subject. In the regular cylinder, the dimensions remain constant and the angle of placement, t, is moved to optimise the output for each subject. Moreover, as the results of this study indicate that the classification is robust to some variation in t from the optimal value, there is no need to customise the system for use with each individual subject.)

In several instances, samples of one postural orientation were classified as two different postural orientations. Partial classification could only occur if the measured vector was approximately equidistant to two nominal vectors (since the subject was not changing orientation during this time). Then the slight fluctuations in the signal would be sufficient to cause the output to change between two classifications. In every case of partial or complete misclassification the subject was classified as being in an adjacent postural orientation.

Conclusion

The algorithm developed and evaluated in this study sub-classified a lying posture into one of four subpostures - lying supine, lying left side, lying face down, and lying right side. A deterministic approach was taken in which the subject was modelled as a cylinder and the TA signal output from each postural orientation was predicted. The measured signal was compared to the predicted signals and the predicted signal that was closest to the measured signal indicated the postural orientation of the subject. The classification accuracy of 92 lying postures taken from 23 subjects was 99%.

6.6.4 Lying—Parameter Extraction

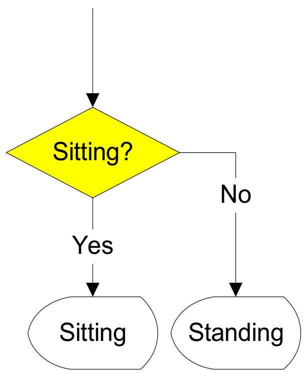
Once a subject has been classified as lying and a subclassification has been made, parameters of interest that can be recorded from the TA are:

- the tilt angle, ϕ of the subject;
- the angle between the x-axis and the vertical (the x-axis tilt angle);
- the angle between the y-axis and the vertical (the y-axis tilt angle);
- the time for which the subject remains in this lying state; and

- the amount of movement as measured by the SMA.

The first three parameters provide further information on the postural orientation of the subject. The duration and SMA of the lying period can be used to develop a picture of the subject's movements and activities over the day.

6.6.5 Classifying Sitting and Standing—A Preliminary Study



Classification of sitting and standing postures.

Introduction

In section 6.6.2 tilt angles were studied for a cohort of 23 normal subjects in lying and upright postures. The upright postures consisted of standing, sitting in a lounge chair, sitting in an office chair, and sitting in an office chair while leaning forward over a keyboard. Figure 6.11 showed the mean z-axis values for each of these states. The z-axis values are the arccosines of the tilt angles. It can be seen that the mean z-axis value was different for each case. The mean value was greatest and the standard deviation smallest when subjects were standing. The mean z-axis value when sitting in an office chair was slightly less than that when standing, but the entire range of standing z-axis values was contained within one standard deviation of the sitting values. The mean z-axis value was smallest when subjects were sitting in the lounge chair. The expected z-axis value when sitting in a lounge chair was significantly less than the expected value when standing ($p < 0.05$). It can be seen from the figure that there was no overlap in the error bars (marking one standard deviation) of the two states.

The difference in z-axis values when sitting in the office and lounge chairs was due to differences in postural orientation. In the office chair subjects tended to sit upright whereas in the lounge chair subjects reclined.

It can be seen from these results that there are some circumstances in which a subject can be identified as sitting from the z-axis value alone, but that there are other upright postural orientations in which the subject's posture cannot be determined from the z-axis value alone.

Subjects can be successfully classified as either sitting or standing on the basis of accelerometer signals when instruments are attached to both the waist and the thigh [19, 37, 72]. As demonstrated, this is not always possible using only a waist mounted accelerometer. However, it was hypothesized that discrimination between the two states could be achieved with only a waist mounted TA by examining the movements of the subject leading up to, during, and immediately following the upright resting state, together with paramters of the resting state such as duration. For example, if the activity immediately before the upright resting state was known to be a transition from standing to sitting then the resting state could be classified as sitting.

The purpose of this study was to develop and evaluate a rule-based algorithm for discriminating between sitting and standing.

Algorithmic Development

As discussed, there are a range of z-axis values that indicate that the subject is sitting and not standing. The first task of the study was to determine the maximum tilt angle that could be achieved by a standing subject. Once this value was determined, then any upright postures with a greater tilt angle could immediately be classified as sitting.

Testing was conducted on two normal subjects, one male and one female, both aged 29 years. The TA was attached to the waist above the right anterior superior iliac spine. The subject was asked to stand upright and then to lean forwards, sideways and backwards as far as possible without overbalancing. The subject was required to maintain each pose for 30 s. This procedure was then repeated but this time the subject was permitted to lean against a wall for support while leaning. The difference between the upright tilt angle and the leaning tilt angles were calculated.

Angular displacement was used rather than absolute tilt angle because the value of the measured tilt angle when standing was dependent on subject and device placement. In figure 6.11 it can be seen that one standard deviation in z-axis values during standing is from 0.929 to 0.978, which corresponds to a tilt angle range of $12.0°$ to $21.7°$. If the tilt angle of the subject standing upright is known, then a measure of the actual tilt of the subject is obtained by taking the difference between the upright tilt angle and the measured tilt angle.

The mean angular displacement from the upright for the subjects were $11.2°$ for the female subject and $7°$ for the male subject. The maximum angular displacement that was achieved occurred when the subjects were leaning forward and using the wall for support. In this instance the maximum angular displacement was $22°$ from the upright value for both of the subjects.

The maximum displacement of $22°$ was achieved in an artificial setting in which subjects were purposely leaning at an uncomfortable angle and using a wall for support. It was assumed that this angle exceeded the maximum angular displacement that would be achieved during standing in normal daily living. Consequently, an angular displacement of $20°$ was set as the maximum that could be achieved by a standing subject.

If the angular displacement was greater than this threshold and the subject was upright, then the subject was classified as sitting. If the angular displacement was below the threshold then the subject could be either sitting or standing. However, the likelihood of the subject being in a sitting posture increased as the angle at which the subject was leaning increased.

This situation was modelled by two probability equations:

$$P(sit) = \begin{cases} 0.5, & 0 \leq T < 5 \\ \frac{T}{30} + \frac{1}{3}, & 5 \leq T < 20 \\ 0, & T \geq 20 \end{cases} \tag{6.1}$$

$$P(std) = 1 - P(sit) \tag{6.2}$$

where T is the angular displacement in degrees.

Six other factors were identified for use in discriminating between sitting and standing. These were the duration of the resting state, the SMA of the resting state, the previous activity, the next activity, the previous resting state and the next resting state. Figure 6.14 shows a block diagram of the system, which was a rule-based classifier. In the classifier, angular displacement, duration, SMA, activity and rest were decoupled and processed separately. A probability for sitting and a probability for standing were obtained from each processing block. The probabilities were then combined and an overall probability for each state was obtained. The state that had the greater probability was given as the output of the classifier.

Resting state duration was included as a parameter because it is unlikely that a subject would remain standing without moving for long periods. As the duration of the rest period increased so did the likelihood that the subject was sitting. This situation was modelled by two probability equations:

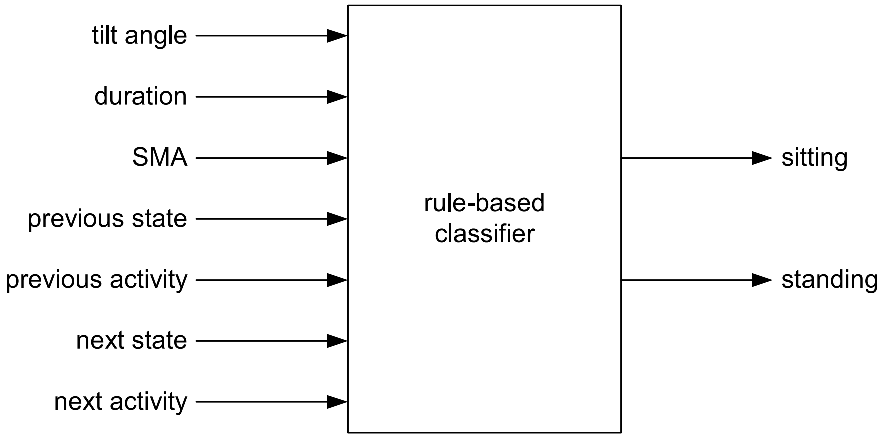


Figure 6.14: A rule-based classifer for distinguishing between sitting and standing.

$$P(sit) = \begin{cases} 0.5, & 0 \leq D < 10 \\ \frac{D}{50} + 0.3, & 10 \leq D < 30 \\ 0.9, & D \geq 30 \end{cases} \tag{6.3}$$

$$P(std) = 1 - P(sit) \tag{6.4}$$

where D is the duration in seconds.

In section 6.4 the SMA was investigated for lying, sitting and standing postures in normal subjects. Figure 6.15 shows a boxplot comparison between the means of the SMA when sitting and the SMA when standing for this data. Application of the student t-test found that the standing postures had a significantly greater SMA than the sitting postures ($P < 0.05$). Consequently, the SMA was used as a test parameter to distinguish between sitting and standing. This was modelled by the following equations:

$$P(sit) = \begin{cases} 0.9, & S < 5 \\ -0.00842 \times S + 0.942, & 5 \leq S < 100 \\ 0.1, & S > 100 \end{cases} \tag{6.5}$$

$$P(std) = 1 - P(sit) \tag{6.6}$$

where S is the SMA expressed as a percentage above the known sitting SMA magnitude.

The previous and next resting states and activities can be used to build up a picture of the movement of the subject. This can be used to deduce the postural

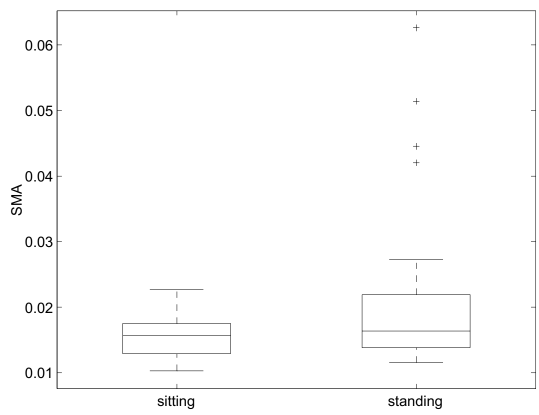


Figure 6.15: Boxplot showing the mean SMA values for subjects when sitting and when standing ($N = 26$).

orientation of the resting state. If the previous or next activity is identified as a transition between two upright postures then the resting state can be determined with the same confidence as the transition identification. If the previous or next activity is identified as walking, then the current state can be identified as standing.

If both the previous and the next resting states are sitting then it is likely that the current state is also sitting as it is unlikely that the subject would stand up and then sit down again without moving anywhere. It is more likely that the subject has adjusted her or his seating position. The inverse assumption cannot reasonably be made, that is, that if the previous and next states are standing then the current state is also likely to be standing.

These heuristics were incorporated into a set of equations for determining the probabilities of sitting and standing from the previous and next activities and a set of equations for determining the probabilities of sitting and standing from the previous and next resting states.

A flowchart of the decision system with the functions that were initially used is shown in figure 6.16.

The algorithm as it is shown in figure 6.16 requires retrospective analysis because it asks for the next activity and the next states as inputs. A modified version of the algorithm was developed that could operate within 30 s of the commencement of the rest state. The 30 s delay is to allow sufficient data collection time for the duration processing block. In the modified algorithm, the inputs N and NS were removed from the system. This was achieved by changing processing block $B4$ to the block shown in figure 6.17 and removing block $B5$ altogether.

In both cases, the classification was made by computing the average probability

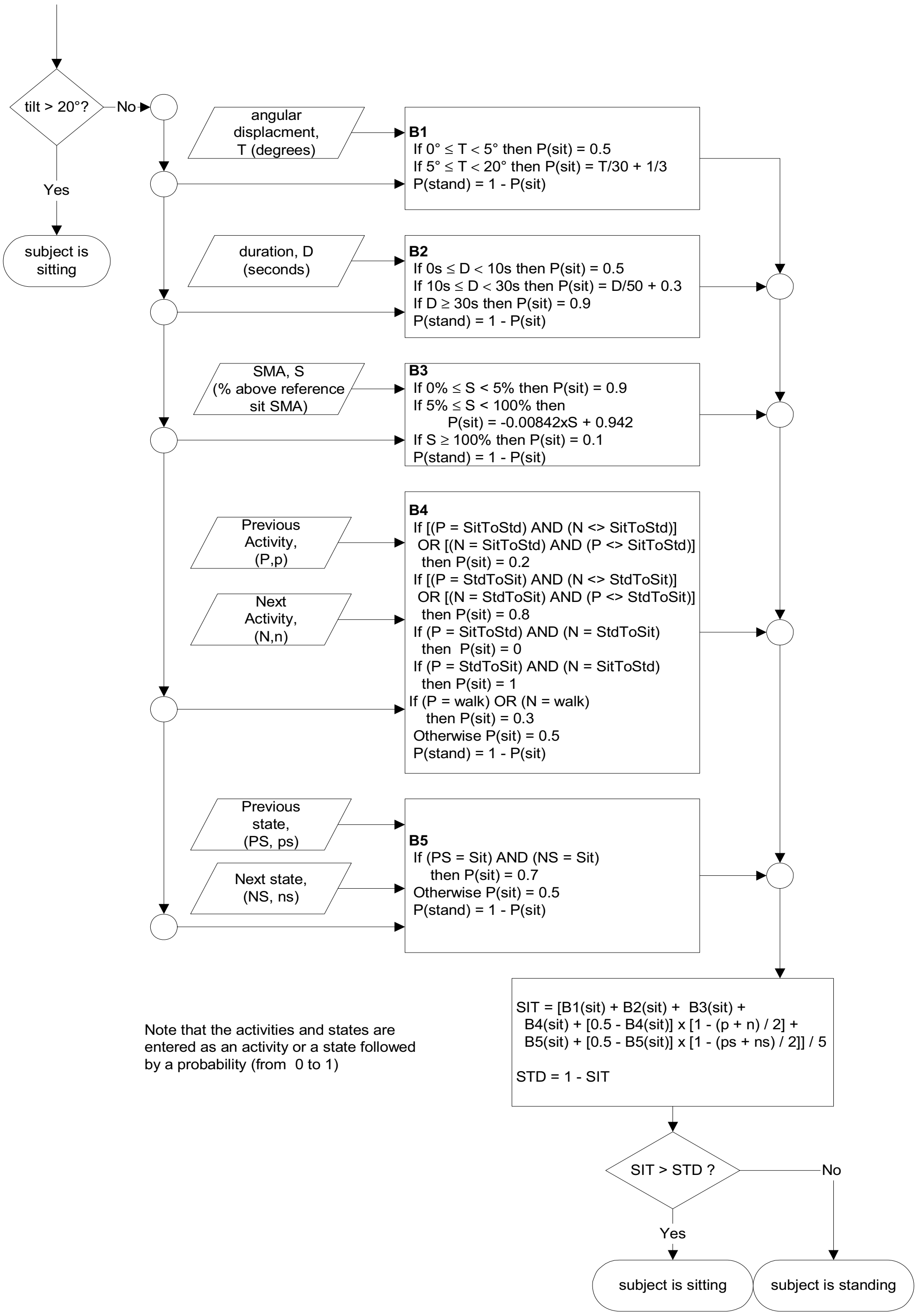


Figure 6.16: Flow diagram of the rule based sit/stand classification algorithm

of sitting and standing from the processing blocks. These were compared and the posture with the greater probability was chosen as the output of the classifier.

Preliminary testing of the algorithm was carried out using a data set taken from normal subjects in a laboratory setting. This provided some measure of the expected performance of each of the components of the classifier.

Experimental Procedure

The data set that was described in section 6.5 was used in this study. Data were obtained from 26 normal subjects sitting, standing and walking in a laboratory setting by means of a single TA attached at the waist, above the right anterior superior iliac spine.

Data Analysis

The activity detection algorithm (section 6.5) was applied to the data to distinguish between periods of activity and periods of rest. The parameters that were used were $n = 3$ samples, $th = 0.135\ g$, and $w = 1.0\,\mathrm{s}$. This set of parameters performed well in the activity detection algorithm but was not optimal. This had the effect of introducing a small number of false positive detections. These were permitted in order to add some variety to the sequence of movements, so that the activities adjacent to a given period of rest could be varied and the algorithm tested under these conditions.

The actual classifications of each activity and each rest period were known by the investigator. Each activity was manually labelled as either a sit-to-stand transition, a stand-to-sit transition, walking or noise. This information was provided to the algorithm, together with classification certainties for each of these classifications.

```
B4
If (P = SitToStd)
  then P(sit) = 0.2
If (P = StdToSit)
  then P(sit) = 0.8
If (P = walk)
  then P(sit) = 0.3
Otherwise P(sit) = 0.5
P(stand) = 1 - P(sit)
```

Figure 6.17: Modified rule set that does not rely on knowledge of the future for processing.

Periods of walking were given a classification certainty of 1.0. Transitions were given a classification certainty of 0.7. Periods of noise were left unclassified. These classification certainties were selected based on the performance of the walking detection algorithm (section 6.8.4) and the sit-to-stand and stand-to-sit transition classification algorithms (section 6.9.4).

The heuristic rules employed in this algorithm were based on expected behaviour of a free-living subject but the sequence of the activities and the durations of each movement in the data set were dictated by the experimental protocol. This meant that the duration of the resting state could not validly be used in this analysis and was excluded.

One standing period was randomly selected for each subject. The median z-axis value over this period was obtained and used as an upright standing tilt angle reference for that subject. This period of standing was excluded from the subsequent classification analysis. The difference between the mean tilt angle in each resting period and this reference angle was used as the angular displacement.

The SMA was computed for the first period of sitting for each subject. This value was used as the sitting reference SMA. This period of sitting was excluded from the subsequent classification analysis. The SMA of each of the remaining rest periods was compared to the reference SMA and the ratio of the two was provided to the classification algorithm.

The probabilities of sitting and standing made by each of the processing blocks $B1$, $B3$, $B4$ and $B5$ for each upright resting state were recorded. The overall probability of sitting was computed as

$$P(sit)_{av} = \frac{P(sit)_{B1} + P(sit)_{B3} + P(sit)_{B4} + P(sit)_{B5}}{4}. \tag{6.7}$$

The classifications made by the algorithm were compared to the actual postures. The system performance was evaluated in terms of the overall classification accuracy and the contribution of each input parameter.

Preliminary Results

The system classified 81 periods of sitting and 174 periods of standing.

The classification results are given in table 6.5. The tilt angle block, $B1$ classified 27% of postures and left the other 73% unclassified. All sitting postures were correctly classified or were left unclassified. 13 (7.47%) of the standing postures were classified as more likely to be sitting, with a mean probability of 0.62 ($\pm$0.13 standard deviation). In these instances the subject had an angular displacement that was greater than 5° from the measured reference upright tilt angle.

Block $B3$, the SMA processing block, performed very poorly and classified almost every posture as sitting. Further investigation found that there was no statistically significant difference in the SMA values between sitting and standing for this data set. Contrary to the earlier findings, in this data set the mean SMA value for sitting was slightly higher than the mean SMA value for standing.

The modified $B4$ block in which only the past activity was used performed slightly better than the original block in which the past and future activities were used, particularly in the classification of standing postures, where the accuracy was improved from 72.57% to 92.57%.

The overall classification was best when the modified $B4$ block was used and block $B3$ was excluded. This resulted in an overall classification rate of 96.86%. The classification accuracy was similar for classification of sitting (95.16%) and standing (97.70%), although the system had a higher confidence level in its sitting classifications. The mean probability of sitting for the correct sitting classifications was 0.75, compared to a mean probability of 0.60 for the correct standing classifications.

Discussion

Distinguishing between sitting and standing is a simple exercise with piezoresistive accelerometers attached to the thigh and to the waist because the thigh moves from vertical when standing to horizontal when sitting. The problem becomes much more difficult when only a waist-mounted accelerometer is used.

However, as the results of this study show, sitting and standing postures can be classified using only a single waist mounted TA using a number of parameters derived from the signal. There are several different ways in which these parameters could be processed to make the classification. A rule-based system was chosen for this study rather than a neural network because less training data was required, expert knowledge could be built directly into the system, and the effect of each parameter on the outcome could be measured.

The finding that the standing and sitting SMAs were indistinguishable is in conflict with the result found in section 6.4. This result may have occurred because the duration of each rest period was quite short. Subjects stood quietly when asked to stand, which resulted in low SMAs. When asked to sit, subjects would sit down and then spend some time adjusting their posture until they were in a comfortable sitting position. This period of adjustment increased the mean SMA during periods of sitting. More investigation into the behaviour of the SMA between sitting and standing in free-living environments is required before a decision on its utility in

		correct (%)	unclassified (%)	incorrect (%)
B1 (tilt)	sit	69.14	30.86	0
	stand	0	92.53	7.47
	total	21.96	72.94	5.10
B3 (SMA)	sit	98.77	0	1.23
	stand	4.02	0	95.98
	total	34.12	0	65.89
B4 (past and future activities)	sit	90.12	9.88	0
	stand	72.57	27.43	0
	total	78.13	21.88	0
B4 (past activities only)	sit	91.36	6.17	2.47
	stand	92.57	7.43	0
	total	92.19	7.03	0.78
B5 (past and future resting postures)	sit	0	100	0
	stand	0	98.28	1.7
	total	0	98.82	1.18
Overall (past activities only)	sit	100	0	0
	stand	4.57	0	95.43
	total	34.51	0	65.49
Overall (without SMA & past activities only)	sit	95.06	0	4.94
	stand	97.70	0	2.30
	total	96.86	0	3.14

Table 6.5: Sitting and standing classification algorithm results. Classification results for each of the parameters (tilt angle, SMA, previous and next activity, and previous and next resting state) and overall classification (with and without the inclusion of the SMA) are given. Results are shown as percentage of events (i) correctly classified, (ii) not classified (probability that the subject is sitting = probability that the subject is standing = 0.5), and (iii) incorrectly classified.

this context can be reached.

If the previous activity was known with certainty then the resting state could be classified with certainty. The ability to do this is limited by the accuracy of the activity classification. There are two possible sources of error here. The first is that an activity is unknown or incorrectly classified. The second is that an activity is not detected. The latter can happen if two or more distinct activities are contained within the same period of activity. For example, if a subject walks to a chair and sits down all in the one movement then the classifier will only detect this as a period of walking and fail to identify the stand-to-sit transition. For these reasons the classification cannot rely solely on the surrounding activities.

Knowledge of the prior and subsequent rest states was not helpful in identifying the current rest state. A more sophisticated knowledge of the subject's movement patterns would be required before this information could be used to predict the current state. Probabilistic modelling techniques, such as Markov chains could be considered for this application once sufficient longitudinal data were collected on the subject.

There are occasions upon which the classifier needs to make a decision based only on present and past events. For example, if a subject collapses into a chair, classification needs to be made without waiting for the subject to move again. On other occasions, if a classification is uncertain, it can be made more certain retrospectively once movements following the period of rest have occurred. In an unsupervised monitoring system the algorithm should make a classification based on past data only. If the classification certainty is low then the classification can be reviewed once more data becomes available.

The system had a higher level of confidence in its sitting classifications. This was because there was more information available for classifying a signal as sitting than there was for classifying a signal as standing. The durations and tilt angles exhibited by standing signals are subsets of those exhibited by sitting signals (figure 6.18). Thus there are occasions when a posture can be classified as sitting with certainty, but the same is not true for standing postures. This is reflected in the levels of decision confidence of the system.

In this study the processing blocks were decoupled, and all blocks were given equal importance in the final vote. The algorithm may be able to be enhanced by permitting interactions between the inputs. One way of effecting this is to allow the voting weights of the blocks to change. For example, if the subject has been in the same resting state for several minutes, it is highly likely that the postural orientation is sitting. This information is conveyed by block $B2$, and so, as the du-

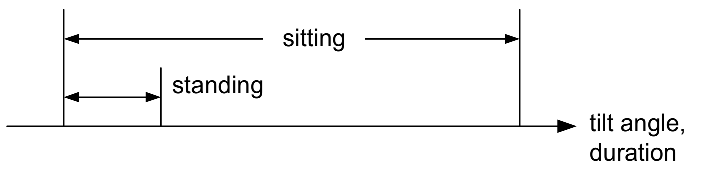


Figure 6.18: Relationship between tilt angle, duration, sitting and standing.

ration increases, the weight given to the block $B2$ output in the vote could increase accordingly. This should be the subject of a future investigation.

The main limitation of this study was that it was conducted in a controlled setting that did not allow testing of the rules in their designed setting. The set and ordering of activities, and the durations of the rest periods were all artificially constructed and did not necessarily reflect those of a free-living subject. Some compensation for this was made when the activities were manually classified. The walking activities were classified with a certainty of 1.0 because walking is a distinctive activity that can be reliably identified using the walking detection algorithm of section 6.8.4. The probabilities indicating the certainty of correctness of the transitions were set at 0.7. The transition algorithm was able to correctly identify the transitions with a much higher accuracy under these controlled conditions (refer to section 6.9.4), but its performance in the uncontrolled home environment was expected to be reduced due to the addition of noise and additional, unclassified movements. The value of 0.7 was used in this study in order to reflect some of this uncertainty.

Despite this difference in setting, this study was successful in demonstrating that sitting and standing states can be determined using only a waist mounted TA by means of a heuristic rule-based classifier. The next stage of the work is to apply this algorithm to distinguish between sitting and standing in a free-living subject. This is discussed in section 7.7 where the entire classification algorithm is applied to data taken from a free-living subject at home.

Conclusion

This study demonstrated that sitting and standing postures can be distinguished using data from a single waist-mounted TA. A heuristic algorithm was applied to a data set taken from twenty-six subjects who carried out a routine of sitting, standing and walking. Periods of sitting and standing were classified with 97% accuracy using the tilt angle and knowledge of the previous activity.

6.6.6 Sitting—Parameter Extraction

Once a subject has been classified as sitting, parameters of interest that can be recorded from the TA are

- the tilt angle, ϕ of the subject;
- the time for which the subject remains sitting; and
- the amount of movement as measured by the SMA.

The tilt angle is useful in that it gives an indication of whether the subject is sitting upright or is reclining or is slouched forward. The duration of the sitting period can be used to build up a template of the subject's daily routine that includes the amount of time spent sitting. The SMA is a useful measure as it indicates the metabolic energy consumption of the subject. It also indicates whether the subject is sitting quietly, or whether there is some movement during the period of rest.

6.6.7 Standing—Parameter Extraction

Once a subject has been classified as standing, the parameters of interest that can be recorded from the TA are

- the tilt angle, ϕ of the subject;
- the time for which the subject remains standing;
- the amount of movement as measured by the SMA; and
- the amount of postural sway.

These parameters are the same as those recorded during periods of sitting, with the addition of postural sway. Measurement of postural sway with a waist mounted TA is discussed in the following section.

6.6.8 Measurement of Postural Sway—A Preliminary Study

Introduction

The most significant parameter when standing is postural sway. It is hypothesized that a TA can be used to measure postural sway in both the antero-posterior and the medio-lateral directions, and that the frequency of the sway is equal to the frequency of oscillation in the acceleration signal, and that the amplitude of the acceleration signal provides a measure of the magnitude of the sway.

In preliminary studies Mayagoita *et al.* [163] and Kamen *et al.* [112] found that an accelerometer attached at the sacrum was able to differentiate between different balance tasks during quiet standing. Kamen *et al.* also demonstrated the repeatability of results by repeating each test thirty times on each subject over a three day interval. They also found that the results obtained from the low back were more consistent than the results obtained from the shoulder, knee or forehead.

The following preliminary study was undertaken to assess the feasibility of measuring postural sway using a triaxial accelerometer mounted at the waist, above the right anterior superior iliac spine. The purpose of the study was to establish whether or not differences could be observed in the measured TA signals under different balance conditions.

Experimental Procedure

One female subject (age 29 years) with no balance or gait impediments wore a TA attached at the waist above the right superior anterior iliac spine. The experimental procedure had 6 components.

(a) The subject stood as still as possible on a firm, level surface with eyes open for 60 s.

(b) The subject stood as still as possible on the same surface with eyes closed for 60 s.

(c) The subject stood as still as possible on a soft block of foam with eyes open for 60 s.

(d) The subject stood as still as possible on the same foam block with eyes closed for 60 s.

(e) The subject stood on the firm, level surface for 60 s. The subject was asked to sway vigorously in the forward-backward direction. The subject was monitored by an investigator and the time at which the subject reached the forward-most point of each oscillation was recorded by the investigator using a stop watch. In this way the period and number of oscillations were measured.

(f) The subject stood on the firm, level surface for 60 s. The subject was asked to sway vigorously in the left-right direction. The time at which the subject reached the right-most point each oscillation was recorded by the investigator using a stop watch. In this way the period and number of oscillations were measured.

The first four tests were then each repeated a further ten times.

Data Analysis

The first 5 s were discarded from the start of each signal. The remaining data were median filtered, filter length $n = 3$ samples. The signals were transformed by rotation about the vertical axis to obtain signals that corresponded to the antero-posterior and medio-lateral axes of the subject as seen by a TA mounted at the sacrum. The angle of rotation was 135°. Fast Fourier transforms were computed for each signal. The frequencies of any peaks in the Fourier transform were measured. The mean, range and SMA were calculated for each signal.

The variability in the results across the ten repeat trials was computed. The first trial was excluded from this analysis to avoid including any learning effects that may have occurred.

Preliminary Results

The acceleration signals from the first trials of the six tests are shown in figure 6.19. The results obtained in the first four tests were consistent across all eleven trials. The acceleration range and SMA were most sensitive to the different balance conditions. The mean ranges are shown in figure 6.20. The range increased from test (a) to test (d). The SMAs for the four tests are compared in the boxplots of figure 6.21. The SMA was lowest for test (a) and increased with every subsequent test to test (f) where it was greatest.

In tests (e) and (f), there was agreement between the sway frequencies measured by the investigator and the frequencies obtained from the Fourier transform in the two tests in which the subject was asked to sway (0.26 Hz for the forward-backward sway and 0.30 Hz for the side-to-side sway).

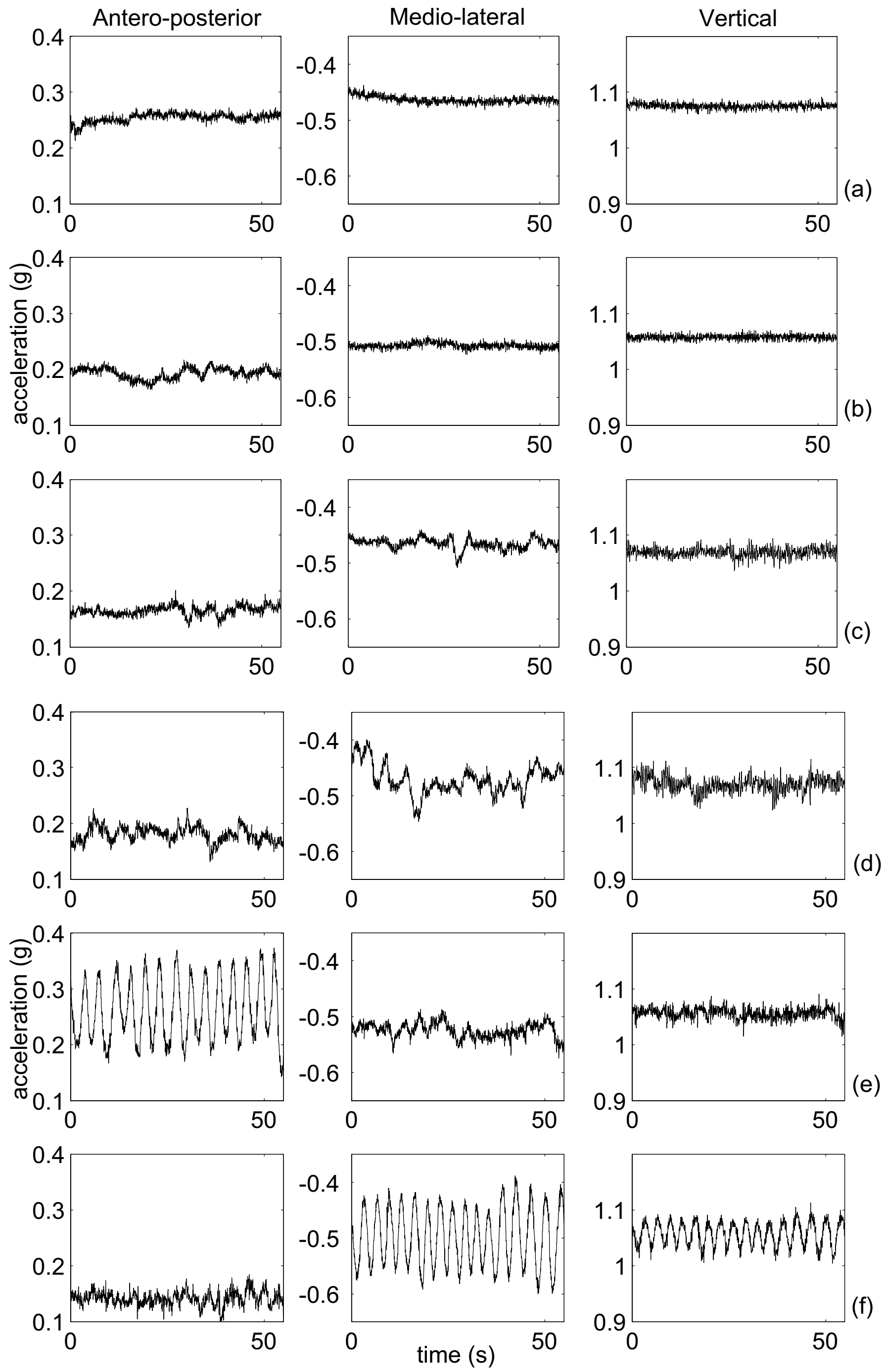


Figure 6.19: Antero-posterior, medio-lateral and vertical accelerations from one subject: (a) standing as still as possible, eyes open; (b) standing as still as possible, eyes closed; (c) standing on foam, eyes open; (d) standing on foam, eyes closed; (e) standing on firm surface with antero-posterior sway; and (f) standing on firm surface with medio-lateral sway. Note the difference in acceleration scales between the three accelerations.

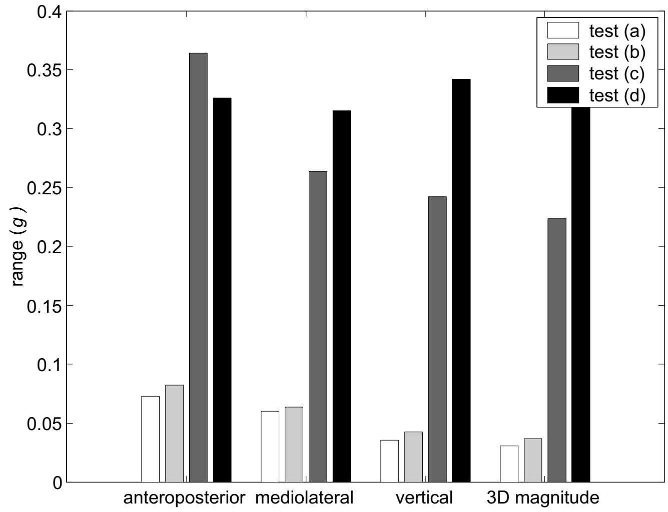


Figure 6.20: Mean acceleration ranges on each axis for ten trials of the first four postural sway tests. Tests were: (a) standing on firm surface, eyes open; (b) standing on firm surface, eyes closed; (c) standing on foam, eyes open; and (d) standing on foam, eyes closed.

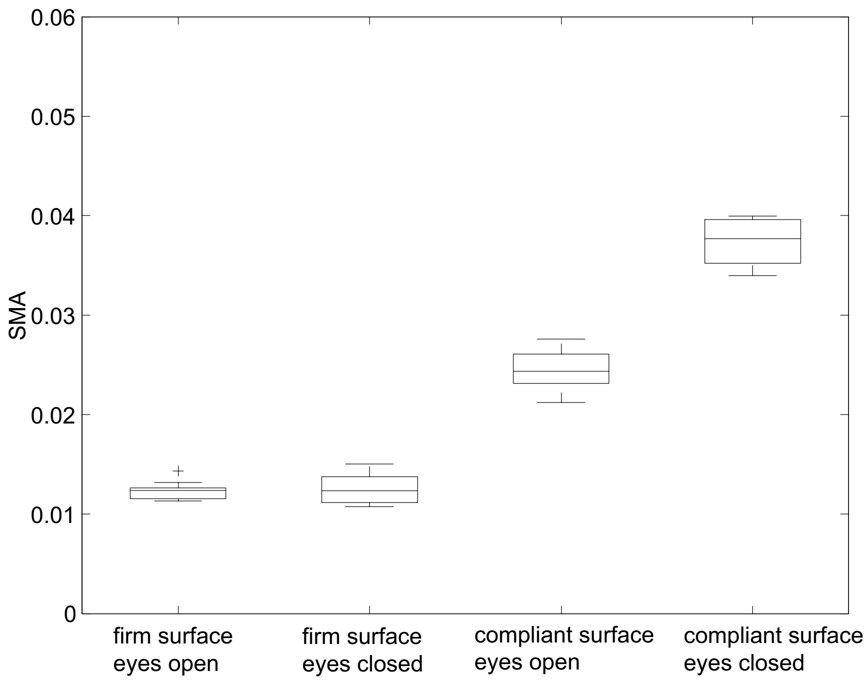


Figure 6.21: Boxplot of the SMA values recorded from ten trials of the first four postural sway tests.

Discussion and Conclusion

The purpose of this study was to assess the feasibility of using a TA mounted at the front-right of the waist to collect measurements of postural sway. The sway frequencies of the periodic oscillations made by the subject in tests (e) and (f) were correctly identified from the Fourier transform of the signal. The increased movement when the subject stood on the compliant surface compared to standing on the firm surface was detected by the TA. This could be seen in the increased acceleration ranges, and in the increased value of the SMA. These results are consistent with the expected results.

The results of this preliminary study lend support to the hypothesis that a triaxial accelerometer attached at the front right is capable of identifying parameters relating to postural sway, and in particular, that the frequency of the sway in a given plane is equivalent to the frequency of oscillation measured by the TA on the appropriate axis, and that there is a relationship between the acceleration magnitude and the magnitude of the sway. An increase in the levels of postural sway led to an increase in both the acceleration range and in the SMA.

These preliminary results indicate that future work in this area is warranted. The next stage of research should involve quantitative validation of the TA as a tool for assessment of postural sway. A study should be developed in which the postural sway of a representative sample of subjects is simultaneously measured with the TA and with an instrument that has already been validated for the assessment of postural sway, such as a force platform or a swaymeter, or preferably both. A methodology for such a study is given in chapter 9.

6.6.9 Conclusion

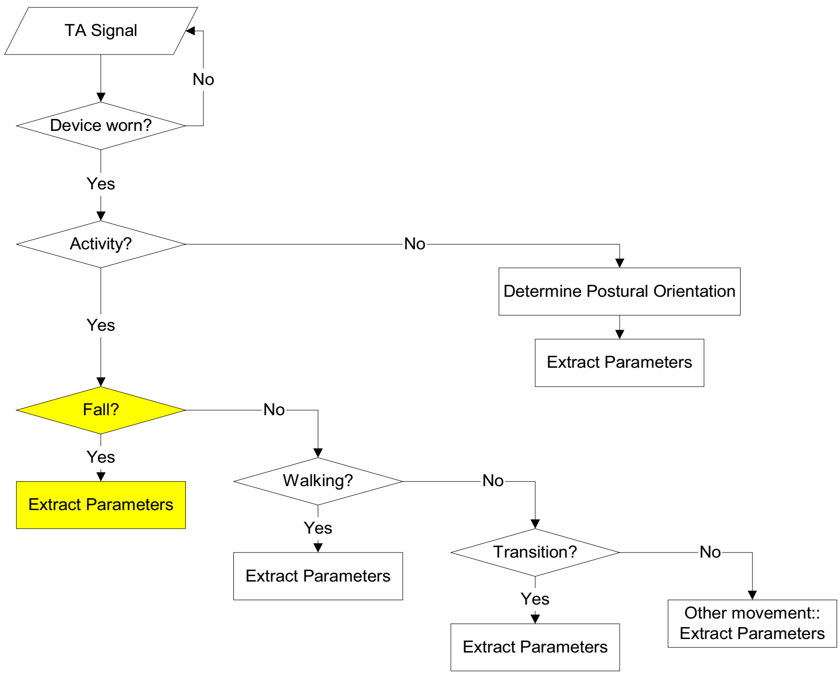
This section has described a set of algorithms for the classification of postural orientation during rest. The posture is classified as either upright or lying and then as one of the subpostures of standing, sitting, lying supine, lying face down, lying on the left side, or lying on the right side.

In studies with normal subjects under controlled conditions, postural orientation was classified as either upright or lying with 100% accuracy. The lying subposture was classified with 99% accuracy. Sitting and standing were classified with 97% accuracy although the controlled conditions and the set routine used in this study affected some of the parameters of interest, including the rest period duration and SMA.

Once the postural orientation has been identified then parameters such as tilt angle, duration, amount of movement and postural sway can be extracted from the signal.

These algorithms have been described in the context of classifying resting states, but their function is not limited to situations in which the subject is not moving. The postural orientation of the subject as described by the tilt angle and the x- and y-axis deviations from the vertical can be identified at any point in time, and hence, during activity as well as rest. It can easily be determined whether or not the subject is upright during any activity, and the tilt angle during this activity can be computed. This is a potentially useful parameter in the assessment of gait and sit-to-stand transitions.

6.7 Classifying Falls



Detection of falls.

6.7.1 Introduction

Falls are one of the most significant problems for elderly people who live alone in the community. Personal alarm systems go some way to addressing the problem by providing the person with a wearable button that, when pressed, enables communication with an emergency response centre. However, after a particularly serious fall, or in the event of unconsciousness, the person may be unable to activate the alarm.

In order to improve the usefulness, reliability and dependability of event monitoring there is a need to automate the alarm detection process [237]. It has been hypothesized that accelerometry is suited to automated falls monitoring [185, 237].

There are many different types of falls. Around the home, common falls include tripping or falling while walking (walking → lying), falling back into a chair while attempting to rise (sitting → sitting), falling into a chair (standing → sitting), slipping over while standing, for example, while showering (standing → lying), and many types of stumbles in which the subject manages to right themselves (standing → standing, or walking → walking). The common feature in all of these events is uncontrolled movement. If the person falls onto the ground or chair the uncontrolled movement leads to large acceleration peaks generated on impact. If the subject stumbles while walking this is likely to produce a large acceleration peak although this may be avoided if the person is able to catch themselves quickly enough. The event will, however, be visible as a disturbance in the gait pattern.

6.7.2 Falls Detection—A Preliminary Study

Introduction

The purpose of the following study was to develop an algorithm that detected large acceleration peaks associated with fall events. As a second task, this algorithm was incorporated into a falls detection algorithm that (i) detected a fall event, and (ii) decided whether an alarm needed to be raised. This study focussed on falls from an upright to a lying orientation. The algorithm was developed and tested using "simulated" falls and stumbles performed by normal healthy subjects.

Experimental Procedure

A data set of "simulated" falls and stumbles taken from two normal, healthy, consenting subjects (one male, aged 31 years, and one female, aged 28 years) was collected for use in developing the fall detection algorithm. Each subject stood or walked around a room, and, while doing so, stumbled or fell onto the floor. The floor of the room was covered with a carpeted surface such as is often found in the home. Eight simulated stumbles during walking and eight falls to the ground from quiet standing or walking were collected.

A second test set of data was collected from two normal, healthy, consenting subjects. One subject was the female who participated in the first data collection. The second was another male subject aged 32 years. These subjects each performed a routine that consisted of

1. two fall to the ground events, remain lying for 60 s;
2. two fall to the ground events, get up again; and
3. two lie down on the ground events, which were performed in a controlled manner.

The events were performed in an order chosen by the subject, and events were separated by normal activity. The routine was carried out in a home environment.

A third data set was collected that consisted of dropping the TA unit to the ground five times. This set contained large acceleration peaks that were not associated with a human fall.

Data Analysis

The first data set was analysed and methods for detecting falls were investigated. All of the stumble and fall events were characterised by large acceleration spikes on at least one of the three axes. The data was first median filtered ($n = 3$) to remove noise spikes, and then three basic methods of detection were tested.

Method 1 involved looking for excessive acceleration magnitudes on each of the x-, y-, and z- axes, and in ρ, the magnitude vector. In order for an event to be recorded the acceleration had to exceed the threshold for a minimum duration. Thresholds between 0.5 g and 1.5 g were considered. Durations between 1 sample and 10 samples were considered. Approaches were tested in which 1, 2, 3, and 4 of the x-, y-, z-axis and ρ signals had to detect an excessive acceleration before an event was logged.

Method 2 involved looking at the magnitude difference between the current acceleration and the running average acceleration over the past few seconds, and the magnitude difference between the current acceleration and the running average acceleration over the next few seconds. If the difference in magnitude exceeded a threshold then an excessive acceleration was recorded. This method was applied to accelerations on each of the x-, y-, and z- axes, and in ρ, the magnitude vector. The running average parameter was varied from 1 s to 10 s. Both mean and median averages were considered. The same procedure was then followed as for method 1. In order for an event to be recorded the acceleration had to exceed the threshold for a minimum duration. Thresholds between 0.5 g and 1.5 g were considered. Durations between 1 sample and 10 samples were considered. Approaches were tested in which 1, 2, 3, and 4 of the x-, y-, z-axis and ρ signals had to detect an excessive acceleration before an event was logged.

Method 3 involved looking for abnormally large signal magnitude areas between successive crossings of the average acceleration magnitude (ρ_{mean}).

The three methods were evaluated and compared using the first data set. The methods were ranked, firstly on the number of events that were correctly detected, and secondly, on the number of false positives that were detected.

The best algorithm was then employed in a fall analysis algorithm. This algorithm is shown in figure 6.22. It firstly identified the occurrence of an abnormally large acceleration using the best of the three methods that were tested. The postural orientation of the subject was determined immediately before and after the large acceleration. If the subject moved from an upright to a lying posture then the movement was identified as a fall. If a fall was not detected then the event was logged and normal processing was continued. If, however, a fall was detected then the subject's SMA and postural orientation were measured for the next 60 s. The SMA was used to determine the amount of movement generated by the subject during this period which could provide an indication of the severity of the fall. If the subject was able to rise again during the 60 s period then the event was logged and an alert was raised to indicate that a fall had occurred. If the subject was still lying after 60 s then the event was logged and an alarm was raised to indicate that a fall had occurred and assistance was required.

This algorithm was tested using data from the second and third data sets.

Preliminary Results

The most successful single method was comparison of the magnitude vector to a preset threshold (method 1). The optimal threshold was found to be 1.8, and the signal was required to exceed the threshold for at least 2 samples. At this level all eight fall events were correctly detected. Four of the eight stumbles were detected, and one false positive was detected.

Although the parameters could be adjusted for the second and third methods so that all fall events were detected, this led to an increase in the false positive rate. In particular, these methods both classified lie/stand transitions as events. Using the third method, normal transitions generated larger SMA peaks than did fall events.

When the method 1 algorithm was incorporated into the falls algorithm illustrated in figure 6.22 and applied to the second data set, there was 100% correct classification for the first subject, with no false positives detected. For the second subject, three of the four falls were detected, and no false positives were detected. Figure 6.23 shows the magnitude signal data taken from the two subjects performing the routine of four falls and two stand-to-lie transitions. The 1.8 g threshold is

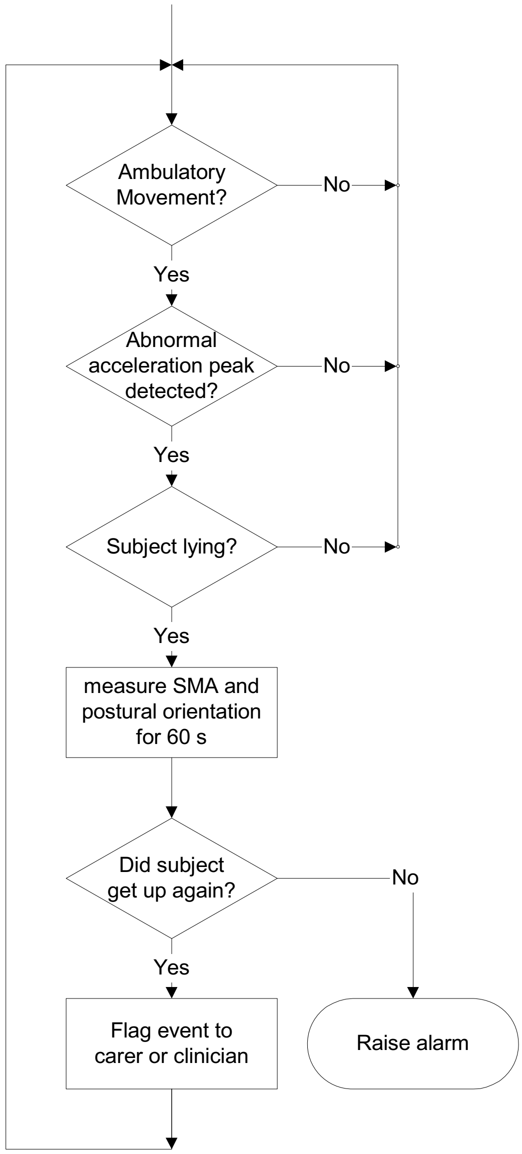


Figure 6.22: Flowchart showing the fall processing algorithm.

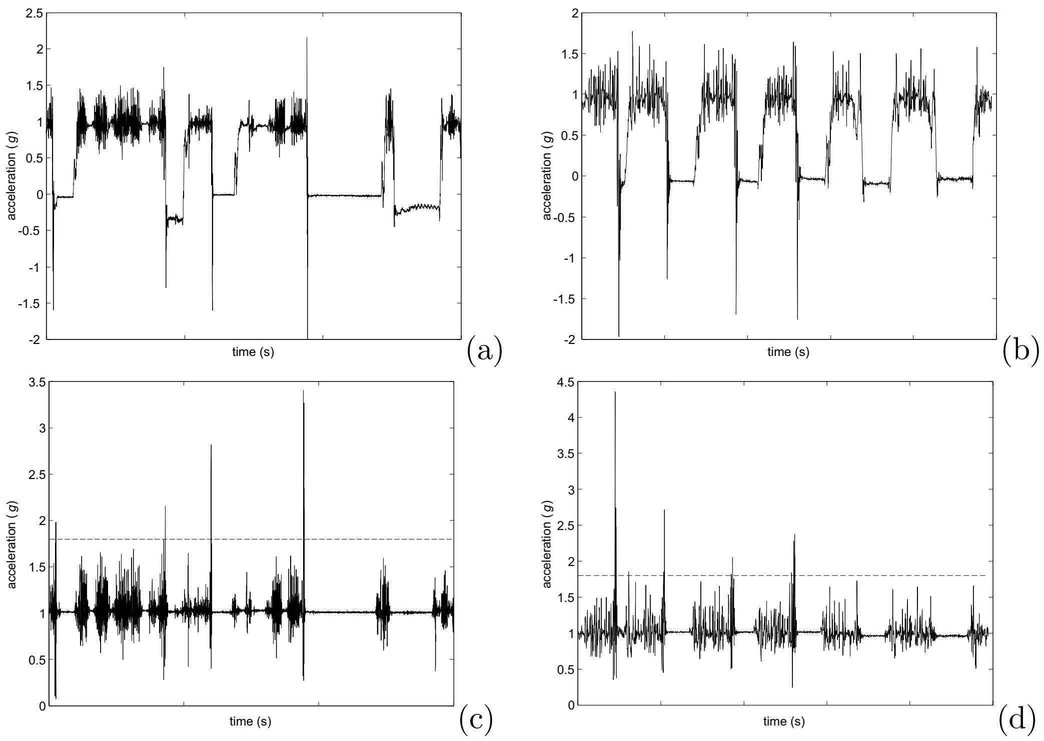


Figure 6.23: Signals obtained from a routine containing four falls. (a) Subject 1, z-axis acceleration, (b) Subject 2, z-axis acceleration, (c) Subject 1, ρ, and (d) Subject 2, ρ. The fall detection threshold is shown as a dashed line in graphs (c) and (d).

indicated. It can be seen that all of the falls, and no other activities, exceed the fall detection threshold.

The signals generated by dropping the TA unit were processed by this algorithm. All five of the drops were detected as falls. Three of the movements in which the TA was picked up were also detected as abnormally large acceleration peaks by the algorithm.

Discussion

The algorithm that was developed was able to detect falls from the acceleration signal. In this preliminary study a fixed threshold was used. In free-living, unsupervised monitoring it would probably be more appropriate to use an adaptive, subject-dependent threshold. This threshold could be determined as a function of the peak walking magnitude acceleration for the subject. This would make the fall detection more sensitive for lightweight subjects and more robust for subjects who generate large accelerations while moving about. It would also ensure that the falls detection algorithm adapted to retain optimal detection sensitivity and specificity if the functional status of the subject changed, leading to a change in the acceleration amplitudes generated.

In the fall event that was not detected by the algorithm, the threshold value was exceeded for one sample, was not exceeded for the following ten samples (almost $\frac{1}{4}$ s), and was then again exceeded for two consecutive samples. A possible modification to the algorithm that would allow detection of this fall event is the detection of an abnormally large acceleration for a minimum number of samples within a specified period of time, rather than requiring the samples that exceed the threshold to be consecutive. This requires further investigation with data from genuine falls.

Simulated fall data was used in this study because of the difficulties inherent in obtaining genuine falls data. When a subject falls deliberately, he or she braces for the fall and this may lead to different signals to those obtained from a genuine fall, which is uncontrolled. However, the effect of bracing for the fall is to smooth the acceleration signal, and so reduce the peak accelerations. It would therefore be expected that in genuine falls the acceleration peaks are even higher.

Few people recover immediately after a fall. Rather, most people remain lying for a short time before trying to get up again. The 60 s delay in raising the alarm is to give the subject time to try to get up again, and to identify the extent of any injury before the alarm sequence is started.

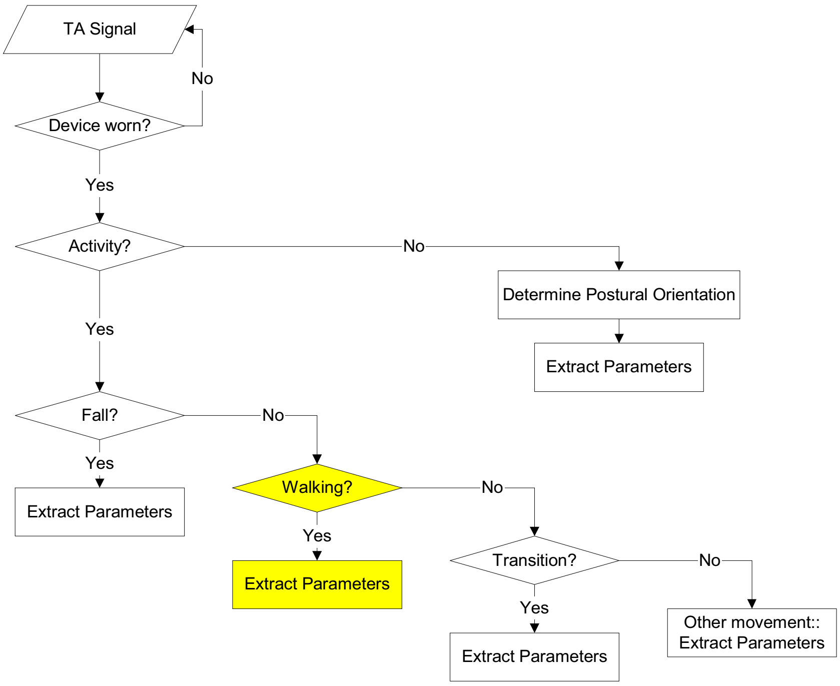
Movements made when the TA unit was not being worn, such as dropping the unit, or picking the unit up after being dropped generated accelerations that were large enough to be detected by the fall detection algorithm. In an unsupervised situation, any fall detection algorithm should be robust enough to detect all falls, but as the sensitivity increases, the likelihood of false alarms also increases. False alarms lead to unnecessary expense and inconvenience, and may lead to the system being disregarded if they occur in sufficient numbers. Hence the alarm should only be raised in the case of a genuine event, not in the case of a false positive detection.

However, as discussed in section 6.4 it is not possible to conclusively distinguish between a motionless subject and a TA that is not being worn. Thus, an instance in which the TA unit is dropped may look like a fall to the classification algorithm. In cases of such uncertainty the system should raise an alarm in case the subject has fallen and is injured, and so it is proposed that a procedural approach be adopted. If the algorithm identifies an alarmable event, the subject is notified via an audible message. In the event of a real emergency, this will act to reassure the patient. In the event of a false alarm, the subject is able to interact with the system to cancel the alarm call.

Conclusion

An algorithm for falls detection was developed in which the magnitude acceleration was compared to a threshold value. Preliminary testing was carried out on a data set of "simulated" falls where it correctly detected seven of eight falls and generated no false positives. The possibility of false positive detections leads to the proposal that procedural methods involving subject interaction be used to allow the cancellation of any false alarms that may be generated.

6.8 Classifying Walking



Classification of walking.

6.8.1 Introduction

Walking is the most fundamental of the daily movements, and one of the most complex. The complexities of gait make it sensitive to early changes in balance and functional independence. Changes such as shuffling rather than stepping, or increased variability in the gait, indicate detrimental changes to health and functional ability that need to be addressed to prevent further deterioration.

A number of studies have found that accelerometry can be used to detect the presence of gait [72, 76, 173, 221, 225]. Gait patterns have been studied manually from TA signals [70]. There has been less work done on algorithmic detection of parameters of gait. Sekine *et al.* [193] developed an algorithm to distinguish between level walking and walking up and down stairs. Aminian *et al.* [18] developed an algorithm to automatically identify gait cycle phases using accelerometers attached to the thighs.

The purpose of this section of work was to identify periods of walking and to identify parameters of gait, in particular, step rate, from the signals of a single TA that was attached at the front-right of the waist. It begins with a study to investigate the use of the Fourier transform to determine gait cadence, a technique that has been used by other researchers [76]. A different technique for determining the step-by-step gait cadence is then presented.

Following these studies of step rate detection, a rule-based gait detection algorithm is developed. Techniques for identifying periods of walking in the signal are discussed and important parameters that can be derived from the signal are described.

6.8.2 Determination of Step Rate using Fourier Transforms

Introduction

Research has found that of the antero-posterior, medio-lateral and vertical acceleration signals, the vertical signal is the one that most clearly shows the stepping sequence [31, 70, 72, 76, 137]. The study described in section 5.4.6 found that this was also the case for the data obtained from a TA unit attached at the front-right of the waist. Fahrenberg *et al.* [72] used a short-time Fourier transform on the vertical axis of a sternum-mounted accelerometer to determine walking step rate.

The questions arise of whether using the vertical axis in isolation is the best way to determine the walking step rate and how good a method the Fourier transform actually is for determining step rate. In this study the average step rate during normal, free walking was determined by means of a fast Fourier transform (FFT). A comparison was made of the effectiveness of using each of the three different signals, and of combinations of the three signals, to measure the step rate.

Experimental Procedure

Twenty-six normal, healthy subjects (seven female and nineteen male), aged between fifteen and forty-nine years, participated in the study. Table 6.6 summarises the physical characteristics of the subjects.

Each subject was tested in a thirty minute session. Each subject performed six tests:

	Mean	Std. Dev.	Min	Max
Gender	7 female, 19 male			
Age (years)	30.7	7.63	15	49
Height (cm)	174.1	9.16	157	192
Weight (kg)	71.7	10.91	53	90

Table 6.6: Physical characteristics of subjects ($N = 26$) participating in the step rate determination study.

- tests 1-4 : the subject was asked to walk at a normal pace along a flat straight 40 m long corridor to the end, and then turn around and walk back down the corridor. This test was repeated two times.
- test 5 : The subject was asked to walk at a normal pace up a typical flight of stairs. There were two landings in the flight of stairs with six stairs below the first landing, nine stairs between the landings and six stairs above the second landing.
- test 6 : The subject was asked to walk at a normal pace down the same flight of stairs.

Each of the tests was timed by an observer using a stop watch. The number of steps taken in each test was counted by the observer. Mean step rate was calculated by dividing the number of steps by the time taken.

Data Analysis

The three signals from the TA unit were high pass filtered to extract the body acceleration component, and median filtered to remove noise spikes. The acceleration magnitude, ρ, was computed. The discrete Fourier transforms of the x-, y-, z-axis and ρ signals were calculated using the Fast Fourier Transform algorithm.

An algorithm was developed to automatically determine the average step rate from the Fourier transform. Normal walking cadence ranges from 95 steps/min (1.5 Hz) to 115 steps/min (1.9 Hz), so the algorithm was designed to look for a frequency peak within the 0.7 to 3 Hz range. The magnitude of the largest signal peak was compared to a baseline noise value. If the signal to noise ratio (SNR) was greater than a fixed threshold value then the frequency at which this peak occurred was identified as the step rate. As a consequence of preliminary testing on earlier data, the SNR threshold value was set to 10. In order to allow for changing noise levels in the signal the baseline noise level was derived from the Fourier transform signal itself, as the r.m.s. value of the signal between 12 and 20 Hz. This range was chosen because 98% of the power in walking is contained below 10 Hz with no amplitudes greater than 5% of the fundamental existing above this frequency [21].

The step rate was determined using

- the x-axis signal alone;
- the y-axis signal alone;
- the z-axis signal alone;
- acceleration magnitude, ρ, alone;
- a voting system in which each component signal had an equal vote; and
- a weighted voting system in which the component signals had unequal votes.

Results

The six walking trials from the 26 subjects resulted in 156 walking records in all. Of these, two of the corridor walking records were discarded. One was discarded because the subject's gait was too erratic (the subject was interrupted by a disturbance in the corridor) and a regular step period could not be determined. The other was discarded because a technical problem with the data logging resulted in loss of part of the data for that trial.

The mean time taken to walk along the corridor was 28 ± 3.6 s (standard deviation). Thus, the mean walking rate along the corridor was $1.4 \pm 0.20\,\mathrm{m.s^{-1}}$. The mean time taken to walk up the stairs was 18 ± 3.3 s. The mean time taken to walk down the stairs was $17\,\mathrm{s} \pm 5.2\,\mathrm{s}$.

Figure 6.24 shows typical examples of the signals obtained from a subject walking along the corridor, together with their Fourier transforms.

Visual analysis found that, of the four signals, step rate was most clearly identified from the z-axis signal. In the Fourier transforms of the x and y signals, a significant component of the signal energy was present in harmonics and in a signal at half the mean walking rate (at the gait cycle frequency). The peak corresponding to the step rate was less easily distinguished in these signals than in the z-axis signal where most of the signal energy occurred at the stepping frequency.

The values computed by the automated algorithm were compared to the measured walking rates with the results shown in table 6.7. For each trial, the automated

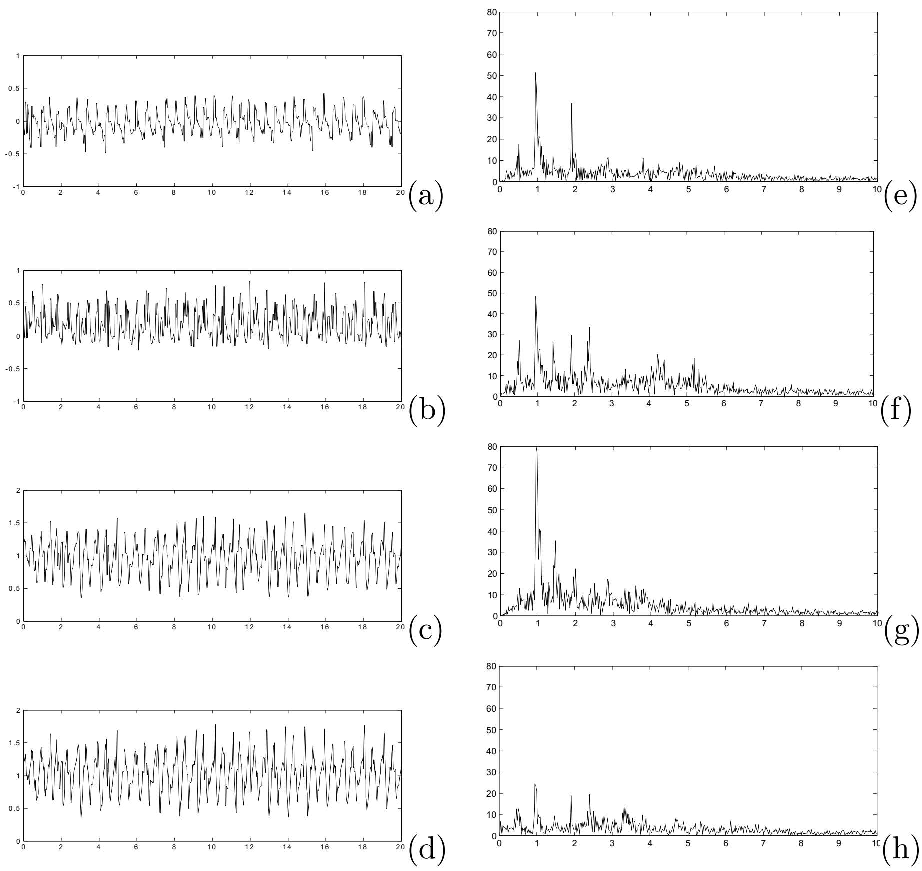


Figure 6.24: Typical acceleration signals from a subject walking along the corridor. (a), (b), and (c) show the x-, y-, and z-axis acceleration signals, respectively, (d) is the magnitude signal, ρ, (in units of g) versus time (in seconds), and (e), (f), (g), and (h) show the corresponding Fourier transforms (in hertz).

algorithm attempted to determine the step rate. If the value determined by the automated algorithm was within 0.2 Hz of the measured value then the algorithm was deemed to have correctly identified the step rate. If the algorithm did not correctly identify the step rate then the erroneous identification was placed in one of four categories:

Type 1: computed frequency $= \frac{1}{2}\times$ actual frequency;

Type 2: computed frequency $= 2\times$ actual frequency;

Type 3: computed frequency = some other frequency; or

Type 4: no frequency computed (no sufficiently large peak in the Fourier transform signal)

The spherical coordinate magnitude vector, ρ, performed poorly, correctly identifying only 40% of step rates. In one third of cases, the algorithm was unable to identify a peak in the Fourier transform signal that corresponded to walking, while in a further 20% of cases, the two-step frequency resulted in a larger peak than the single-step frequency. When x- or y-axis signals were used, the algorithm performed reasonably, achieving overall accuracies of 63% and 74% respectively. However, when the z-axis signals were used, the algorithm performed very well, correctly identifying 96% of step rates. 100% of step rates were correctly identified when subjects were walking along the level corridor or walking up the stairs. Six of the twenty-six trials in which subjects walked down the stairs were misclassified and all but one of these were classified as type 3 errors.

The voting systems that were tested performed better than using only the x-axis, y-axis or ρ signals but did not perform as well as simply using the frequency determined from the z-axis signal. Figure 6.25 compares the results of the best median voting system, the best weighted mean voting system, and the results obtained from the individual signals.

Discussion

All of the subjects exhibited a regular step rate when they were walking along the level corridor. This resulted in large peaks in the Fourier transforms of the signals at the step rate.

Climbing up the stairs also resulted in a regular step rate. However, subjects walked down the stairs in a more erratic manner, typically taking several rapid steps followed by a pause, then several more rapid steps. This variation made it more difficult to determine a mean step rate and led to increased errors in step-rate determination.

Walk		x	y	z	ρ
Along corridor	N	102	102	102	102
	No. correct	80	85	102	35
	% correct	78.4	83.3	100	34.3
	Type 1 error	11	10	0	29
	Type 2 error	0	0	0	4
	Type 3 error	1	7	0	0
	Type 4 error	10	0	0	34
Up stairs	N	26	26	26	26
	No. correct	15	20	26	19
	% correct	57.7	76.9	100	73.1
	Type 1 error	9	6	0	1
	Type 2 error	0	0	0	0
	Type 3 error	0	0	0	3
	Type 4 error	2	0	0	3
Down stairs	N	26	26	26	26
	No. correct	2	9	20	8
	% correct	7.7	34.6	76.9	30.8
	Type 1 error	4	5	1	0
	Type 2 error	0	10	0	0
	Type 3 error	7	8	5	2
	Type 4 error	13	3	0	16
Total	N	154	154	154	154
	No. correct	97	114	148	62
	% correct	63.0	74.0	96.1	40.3
	Type 1 error	24	21	1	30
	Type 2 error	0	1	0	4
	Type 3 error	8	15	5	5
	Type 4 error	25	3	0	53

Table 6.7: Results of the automated classification algorithm. Error types are as follows: Type 1: computed frequency = $\frac{1}{2}\times$actual frequency; Type 2: computed frequency = $2\times$actual frequency; Type 3: computed frequency = some other frequency; Type 4: no frequency computed (no sufficiently large spike in the Fourier transform),

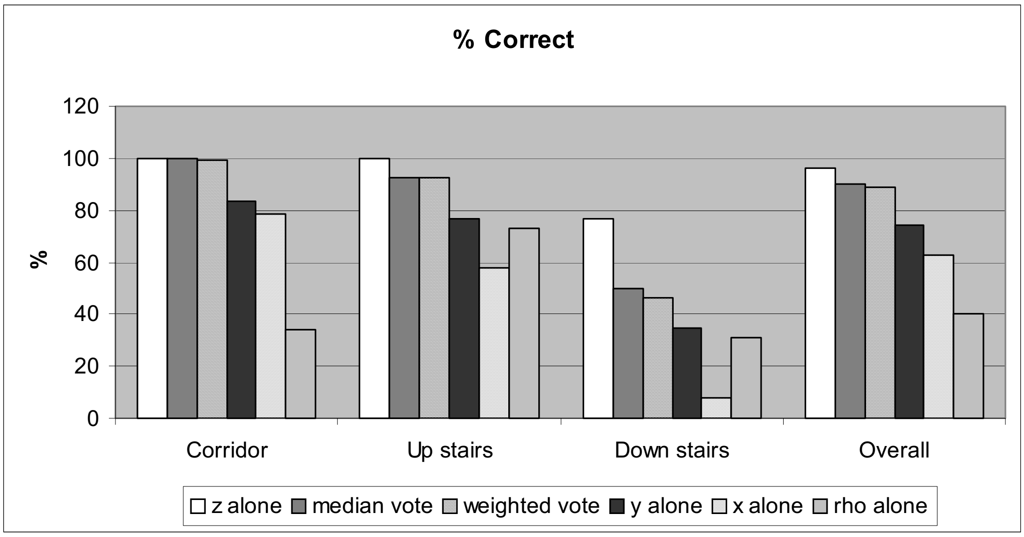


Figure 6.25: Percentage of walking speeds that were correctly identified by each of the x-, y-, and z-axis and ρ signals and two voting systems, a median voting system and a weighted mean voting system.

On five of the six occasions during descent when the mean step rate was incorrectly determined by the algorithm using the z-axis signal, the mean step rate was not correctly determined by any method. On one occasion, use of the y-axis acceleration resulted in correct identification of the step rate when use of the x-axis, z-axis and ρ accelerations resulted in incorrect classification.

This study shows the benefits and limitations of using the Fourier transform to determine average step rate. Peaks occur in the Fourier transform at frequencies that are strongly represented in the signal. A peak representing walking rate will only be detected in the Fourier transform if (i) the walking signal is of sufficient length, and (ii) the walking is regular and the step rate is consistent. If there is large variability in the stepping frequency then the Fourier transform will be less effective in identifying the mean frequency. However, it appears to be a highly effective approach when there is low variability within the step rate, as was the case in the level corridor walking.

Conclusion

An algorithm in which the average step rate was determined from peaks in the Fourier transform of the acceleration signal was developed and tested on data samples taken from 26 normal, healthy subjects walking along a level corridor and up and down a flight of stairs. Methods using the x-, y-, and z-axis accelerations, the magnitude acceleration, ρ, and voting systems that combined the individual outputs were tested. The best results were achieved when the z-axis acceleration was used. The average step rate was determined with 100% accuracy for level walking and for walking up stairs. The average step rate was determined with 76.9% accuracy for walking down stairs. This simple and efficient approach is highly effective in determining the average step rate during regular walking, but its accuracy decreases with increasing step rate variability.

6.8.3 Step-by-Step Determination of Gait Cadence

Introduction

The two limitations of the Fourier transform method are that it is only suitable for gait with a regular step rate and that it can only give a measure of the average gait cadence, not of the step-by-step cadence. This study investigated the application of a new approach to determining step rate during walking. This approach sought to identify a characteristic point in the signal once every gait cycle and, hence, determine the step-by-step gait cadence.

Experimental Procedure

Eight healthy subjects without gait impediment (3 female, 5 male, aged 26–60 years) participated in the study. Each subject attached the TA device at the waist, above the right anterior superior iliac spine and then proceeded to walk about a level circuit. The circuit was around a house (house (b) in figure 4.3). The circuit passed through several rooms of the house and subjects had to navigate through open doorways and around various obstacles such as chairs and tables while walking at a fixed step rate. Each subject walked at least 80 paces at each of 40, 60, 80, 100 and 120 steps/min. The subject walked in time to a metronome that gave an audible "click" at the required step rate.

Data Analysis

The TA signals were median filtered ($n = 3$ samples) and then used in the data analysis.

In section 5.4.6 it was found that steps during gait could be identified manually in the signals from a TA attached at the front-right of the waist. In this study, each step was identified manually in the acceleration signals, using the peak vertical acceleration as the reference marker. The number of samples between each marker was counted and the time between each successive step was computed. This was used as the reference to which the results of the automated step detection algorithm were compared.

The algorithm was applied to each one of the three (x-, y-, and z-axis) signals from the TA. All of the maxima in the signal were identified. One of the maxima was chosen at random. A 41 point (just under 1 s) sample of the signal centred about this point was taken. A sliding window of width 41 samples was applied to the 10 s period of signal following this sample. The correlation coefficient between the signal sample and the signal contained within the sliding window was calculated. If a correlation coefficient greater than a threshold of 0.85 was measured then this sample was retained as a candidate walking template. This threshold value was chosen as the result of preliminary testing of the algorithm with the data set used in the last study (section 6.8.2). If no correlation coefficient greater than the threshold was measured then this sample was rejected and another maxima was randomly chosen, a 41 point sample about this point was taken and the process of correlation testing was repeated.

This procedure was repeated until three candidate walking templates were obtained. Of these three candidate templates, only one was chosen for use as the walking template. The candidate templates were compared in pairs and the correlation coefficient was calculated for each pair. This resulted in two correlation coefficients being associated with each candidate template. These two correlation coefficients were summed and the candidate template that had the highest sum was chosen as the walking template.

A sliding window was then applied to the entire signal. The sliding window had a width of 41 samples and was offset by 1 sample each time that it was applied. The walking template was cross-correlated with the sample of signal inside the sliding window. Maxima in the cross correlation signal that exceeded a threshold value were marked as step reference points. The threshold value was set at 0.5. This result was chosen as the result of preliminary investigations using this method of step determination.

The automated algorithm could choose any point in the step cycle to be the reference marker. In order to allow comparison between the automated algorithm's step identification and the manual step identification, the distance (in samples) between the algorithm's step marker and the peak on the z-axis was measured for a random step. The entire cross correlation signal was shifted by this difference so that the automated algorithm step markers should align with the peaks on the z-axis if the algorithm performed effectively.

If the automated algorithm detected exactly one step within the range $[m - 0.2 \times s, m + 0.2 \times s]$, where m is the sample at which the step marker was manually identified and s is the expected number of samples per step ($s = \frac{45\times60}{step\ rate}$), then this was accepted as identification of that step. If no step was detected in this range then the algorithm failed to detect the step. If more than one step was detected in this range then this was recorded as detection of a false step. Any steps detected outside this range were also classified as false steps. The algorithmically determined mean, standard deviation and median walking rates were calculated for each subject at each walking speed.

The detections from each of the different signals were combined to produce an overall decision on where the step markers should be located. A voting system was used in which, if the majority of the signals detected a step then a step marker was added at that position. If the majority of the signals did not detect a step then no step marker was added. The final result of the step detection algorithm was compared to the actual step sequence and the system sensitivity and specificity were computed for each walking rate.

A three-dimensional version of the algorithm was also tested. In this version the maxima were determined from the z-axis signal. One peak was chosen at random and a 41 sample range about this point was selected. A sliding window was applied to the next 10 s of the signal. The x-axis signal in the sample range was correlated with the x-axis signal in the sliding window, and similarly for the y- and z-axes. The three correlation coefficients were averaged to obtain a test correlation coefficient to compare to the threshold value. The threshold value was again set to 0.85. Three candidate templates were chosen in the same way as for the original algorithm. They were compared by means of the three-dimensional correlation measure described above in order to choose the best candidate template. The x-axis of the walking template was compared to the contents of a sliding window across the entire signal. This was repeated for the y- and z- axes. The three correlation signals were averaged to produce a three-dimensional measure of the correlation. The maxima in the three-dimensional correlation signal were identified, and those exceeding a threshold of 0.3 (chosen as the result of preliminary testing) were identified as step reference markers. From here, the procedure was the same as for the original algorithm.

Results

All of the subjects found a walking speed of 40 steps/min extremely slow. Two subjects found it too slow and were unable to step in time with the metronome at this speed, so data at this walking speed were discarded for these two subjects. All

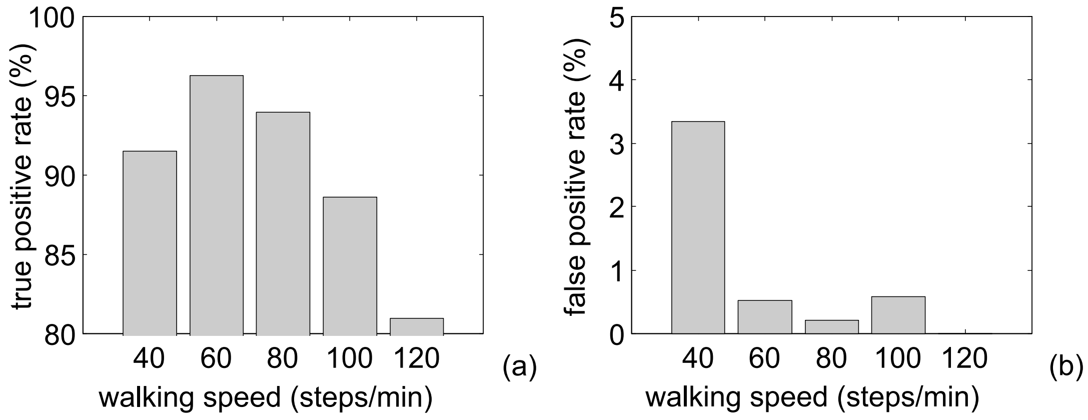


Figure 6.26: (a) true positive rate, and (b) false positive rate (as a percentage of the total number of steps) as a function of walking speed when the most successful template matching technique was applied to 4020 steps generated by 8 normal subjects walking at speeds from 40 to 120 steps/min.

subjects were able to walk at every subsequent speed up to a speed of 120 steps/min which they found uncomfortably fast on this walking circuit. In total, 4020 steps were analysed.

The best step detection performance was achieved using a voting system that combined the decisions of the walking classifier applied to each of the one dimensional signals over three trials. This correctly identified 90.5% of the 4020 steps, with a specificity of 99% and this accuracy increased to 95% sensitivity and 99.6% specificity when subjects were walking at 60–80 steps/min. At every tested step rate the sensitivity exceeded 80% and the specificity exceeded 96%. The results are shown in figure 6.26. The results were best when subjects walked at 60–80 steps/min, which were the most comfortable walking speeds for the subjects.

Discussion

One of the difficulties with step identification from a waist mounted TA is that the acceleration signals are quite individualistic, especially at slow walking speeds and for people with impaired gait. This limits the useability of simple pattern-matching techniques (such as looking for the point of steepest descent, or looking for the highest peak). However, within the one subject at the same walking speed, the gait cycle is highly repeatable, so much so that "it is generally assumed that all successions of the cycle are identical" [108]. Murray [174] found that even highly individualistic components of the gait cycle such as pelvic rotation were prototypes for successive cycles by the same subject.

This template matching step identification algorithm applied in this study achieved high identification rates (90.5% sensitivity and 99.6% specificity) without any assumptions being made about the shape of the gait signal. The algorithm was based on only one premise: that, when walking at a given speed, a subject will take each step with the same foot in the same way [108]. The algorithm requires no information on the underlying shape of the gait signal. Instead, the algorithm chooses its own template, and a new template is chosen for each subject at each walking speed. This gives the algorithm a flexibility that makes it suitable for detection on any repeated pattern within a signal. This approach overcomes the limitations of the Fourier transform algorithm of the last study because it makes no assumptions about the periodicity or the regularity of the gait and so could be applied to a gait with an irregular step rate. Preliminary testing indicates that the algorithm shows promise for application to irregular and pathological gaits.

The algorithm detected both left and right steps when applied to the z-axis. The performance of the algorithm applied to the x- and y-axis signals varied across subjects, but in general, the algorithm strongly detected every second step (i.e. steps made by the same foot) but did not detect the alternate steps so well. This is to be expected because the TA was placed off-centre which means that the signal seen by the TA was asymmetrical and therefore slightly different for a right-foot step compared to a left-foot step, even if the subject's gait was perfectly symmetrical.

A 1 s window was used for the template because 1 s is sufficient time for the characteristic features of the gait (such as the signature heelstrike) to occur, even in a very slow gait. In a rapid gait, more than one step may be contained in this window. However, gait becomes increasingly rhythmical with increasing speed, and so, since the step rate becomes more regular at fast speeds, it does not matter that more than one step is included in the template.

The step template was rigorously chosen to reduce the likelihood of selecting a poor template. Each of the candidate templates was required to have a high cross correlation with the subsequent signal. This meant that it must be a pattern that was repeated in the signal. The candidate templates were then compared to find the template that had the most in common with both of the other templates. This again increased the probability of rejecting a poor template. The system accuracy was significantly improved by repeating the entire procedure three times and then taking a vote to decide on the final step rate.

The procedure used to find the template in the first place was computationally demanding. However, once a template was chosen, the algorithm reduced to requiring only one comparison to be made for each incoming sample, and this could be further reduced by not testing the samples immediately after a step has been identified because there will be a lag of at least half a second before the subject takes the next step during which time there is no benefit in looking for steps. However, if the algorithm is to be used for monitoring of a particular subject over an extended period it may be better to manually choose a template from the signal of a specific walking test rather than randomly choosing the template during arbitrary walking around the home.

A template need only be selected once for a particular subject. Once a suitable template has been chosen, it can be used for analysis of all subsequent periods of walking. Moreover, the cross correlation of the template with the walking signals can be tracked longitudinally to give a measure of change in gait style, as well as information on step rate.

Conclusion

In this study an algorithm for step-by-step determination of gait cadence was introduced and tested on a data set taken from eight normal subjects walking around a house at five different rates. The algorithm detected each step with an overall sensitivity of 90.5% and specificity of 99.0%. This accuracy increased to a sensitivity of 95.0% and a specificity of 99.6% when subjects were walking at 60–80 steps/min. The algorithm automatically chose a template from the walking signal and used this template to identify each step in the signal.

The algorithm was able to identify step-by-step gait cadence, which allows parameters of step rate and variability to be measured, as well as average step rate. The cross correlation between the template and the gait signal can also be tracked over time in order to identify longitudinal changes in the subject's gait style.

6.8.4 Identifying Gait

Introduction

The repeated movement inherent in gait is one important characteristic that can be used to distinguish it from other daily activities such as transitions between postural orientations in which the sequence of movements is executed only once. During walking, the postural orientation of the subject is upright, and close to that of standing. Walking activities tend to have a longer duration than other basic daily activities. A normal person completes a transition within a few seconds, whereas a period of gait must go for at least a few seconds and has no maximum duration. Walking activities also tend to have a larger SMA than the other routine daily activities considered in the current work. Results of data analysis for the activity detection algorithm (section 6.5) found that the average SMA was greater during walking than during sit-to-stand or stand-to-sit transitions.

These four features—repeated movement, duration, postural orientation and SMA—were combined into a rule-based algorithm to identify periods of walking from a TA signal.

Experimental Procedure

A data set of 208 sit-to-stand and stand-to-sit transitions, 130 stand-to-lie, lie-to-stand and lie-to-lie transitions, and 77 periods of walking taken from 23 normal subjects (7 female, 16 male; age 30.5 ± 6.3 years standard deviation) was analysed. Each subject carried out two procedures. The first procedure involved sitting, standing, walking, and moving between the different postural orientations with the TA unit attached at the waist above the right anterior superior iliac spine. This procedure was described detail in section 6.5. The same subjects were then asked to leave the TA unit attached at the waist above the right anterior superior iliac spine and carry out a second procedure. This consisted of (i) standing for 20 s; (ii) lying down; (iii) lying supine for 20 s; (iv) rolling onto the left side; (v) lying on the left side for 20 s; (vi) rolling over to lie face down; (vii) lying face down for 20 s; (viii) rolling onto the right side; (ix) lying on the right side for 20 s; (x) standing up; and (xi) standing for 20 s. This was the same data set that was used in section 6.6.3.

Data Analysis

The algorithm that was developed and applied is illustrated in figure 6.27. The subject needed to be upright to be walking. This was determined by looking at the tilt angle of the averaged z-axis signal over the period of the activity. The criterion described in section 6.6.2 was used (if the mean z-axis value was greater than a threshold then the subject was upright), but the threshold value was increased from 0.5 to 0.8. This was because the posture for walking is closer to the posture for standing than a sitting posture needs to be. The activity was not regarded as walking if it was completed within 3 s. Although the subject may have taken a small number of steps during this period, there was not sufficient time for the subject to travel any distance or for enough data to have been generated for the extraction of parameters of gait.

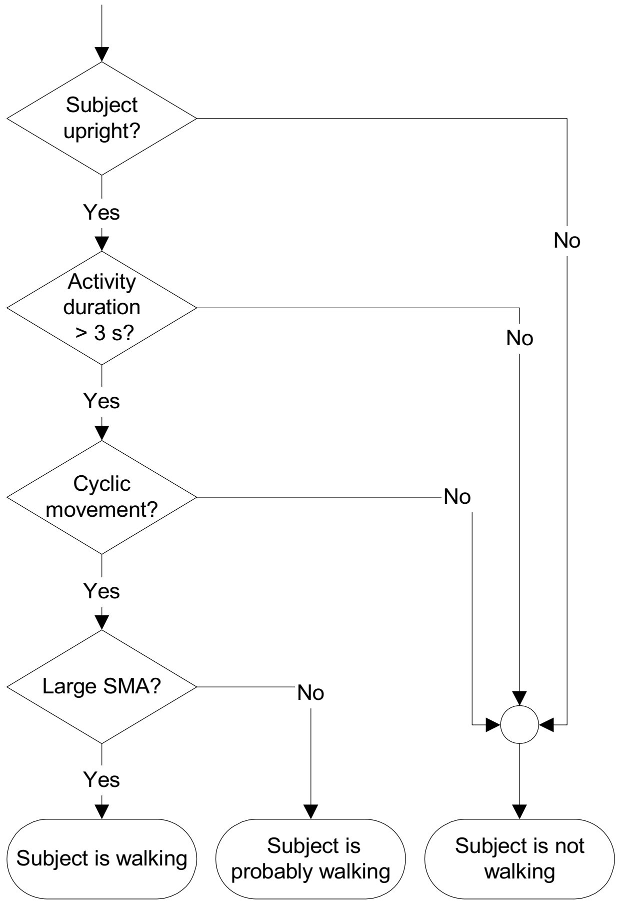


Figure 6.27: Flowchart showing the walking detection algorithm.

If the activity met these first two constraints it was then tested to see whether the signal was of a repetitive nature. For this study, the Fourier transform of the z-axis signal was computed. If there was a peak in this signal in the expected range of walking frequencies such that the signal to noise ratio at the peak was greater than 10 then this was accepted as evidence of a periodic signal. This procedure was described in detail in section 6.8.2. Finally the SMA of the activity was computed.

In a preliminary study the mean SMA values for the walking data, the sit/stand transitions, the stand/lie transitions and the lie/lie transitions were computed. The mean SMA for walking was found to be significantly greater than the mean SMA for the other activities (Wilcoxon rank sum test, $p < 0.001$).

A bootstrapping technique was used in which the mean walking and not-walking SMAs were computed for all subjects except the subject whose data was currently undergoing analysis. If the SMA of the activity in question was greater than the computed mean non-walking SMA then it was classified as a large SMA by the algorithm.

The “subject upright”, “activity duration”, “cyclic movement”, and “large SMA” processing blocks were first applied to every activity to determine their individual effects on the data.

After this the complete walking detection algorithm was used to classify each activity as either (i) not walking; (ii) probably walking; or (iii) definitely walking. These classifications were compared to the actual activities and the accuracy of the system was measured.

Results

When the activities were processed by the “subject upright” processing block all of the transitions that involved a lying posture were excluded. When all of the activities were processed by the “activity duration” processing block 172 of the 338 non-walking activities (50.8%), but none of the walking activities were excluded. When all of the activities were processed by the “cyclic movement” processing block all but 13 of the non-walking activities (3.8%) but none of the walking activities were excluded. When the “large SMA” processing block was applied to each of the activities 35 of the non-walking activities (10.4%) returned a “yes” response and 7 of the 77 walking activities (9.1%) returned a “no” response.

When the activities were processed using the entire algorithm shown in figure 6.27 all 338 non-walking activities were correctly identified as “not-walking”. Of the 77 periods of walking, 70 (90.9%) were classified as “definitely walking”, and 7 (9.1%) were classified as “probably walking”.

Discussion

The Fourier transform algorithm was used to identify cyclic movement in this study because all of the data were taken from subjects with normal gait and this algorithm is very effective in detecting periodic gait (section 6.8.2). However, for a different subject group that may have irregular or pathological gait the template matching algorithm (section 6.8.3) may be more appropriate.

The rule based algorithm developed in this study discriminated between gait and other activities with a high degree of accuracy. Identification of the repetitive nature of the signal was the most powerful single discriminator of gait. Duration was also a useful parameter but the threshold value needs to be set according to the subject cohort in order to reject transitions and other activities of short duration.

For an elderly or disabled subject who moves slowly, the duration threshold would need to be increased to exclude transitional movements.

The SMA was less effective in identifying gait. A large SMA suggested that the activity was walking, but did not guarantee it, and not all periods of walking had a large SMA. A moderately large SMA sustained over a longer duration was a more powerful identifier of gait.

Conclusion

An algorithm was developed to distinguish walking activity from non-walking activity. The algorithm was based on four features of walking: repeated movement patterns, upright posture, longer activity duration, and higher SMA. The algorithm was tested on a data set of walking and routine non-walking activities taken from 26 normal subjects. The algorithm correctly identified all non-walking activity as "not walking". It identified 90.9% of walking activity as "definitely walking" and the remaining 9.1% as "probably walking".

6.8.5 Parameter Extraction

Once a subject has been classified as walking, parameters of interest that can be recorded from the TA fall into two categories. Firstly, step-by-step parameters can be extracted. These include descriptive statistics of step-by-step variability:

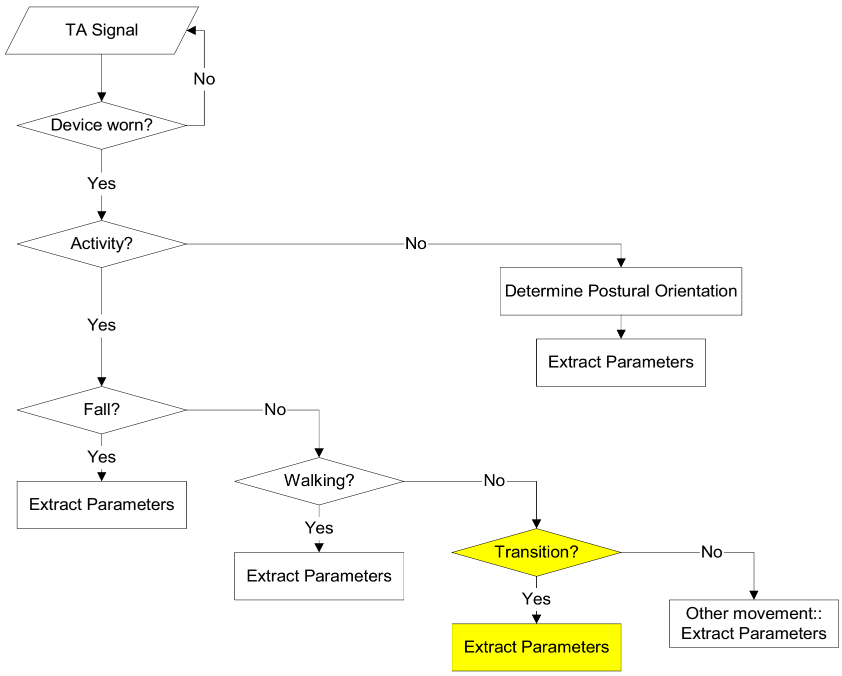
- mean step duration;
- median step duration;
- r.m.s.;
- peak amplitude;
- standard deviations; and
- cross correlations between steps.

Internal step timing variations can also be measured once further work is undertaken to relate the components of the signal from different waist placements to the stages of the gait cycle.

Secondly, parameters relating to the overall period of activity can be determined. These include:

- Overall mean walking cadence;
- the amount of movement as measured by the SMA; and
- the duration of the walking activity.

6.9 Classifying Transitions



Classification of transitions.

6.9.1 Introduction

The time taken to make a transition between two postural orientations provides an important measure of functional ability [122, 172]. The basic types of transitions are changes between sitting and standing, between upright and lying, and between lying subpostures.

In the approach taken here, the postural orientations of the subject before and after the activity are determined, and these are used to decide which transition to test for. Table 6.8 provides a lookup chart of possible transitions based on postural orientation before and after the activity, and figure 6.28 shows a flowchart of the classification process.

before \ after	upright	lying
upright	sit/stand transition	upright-to-lying transition
lying	lying-to-upright transition	lying/lying transition

Table 6.8: Possible transitions based on postural orientation before and after the activity. The before postures are listed in the left column, and the after postures are listed in the top row.

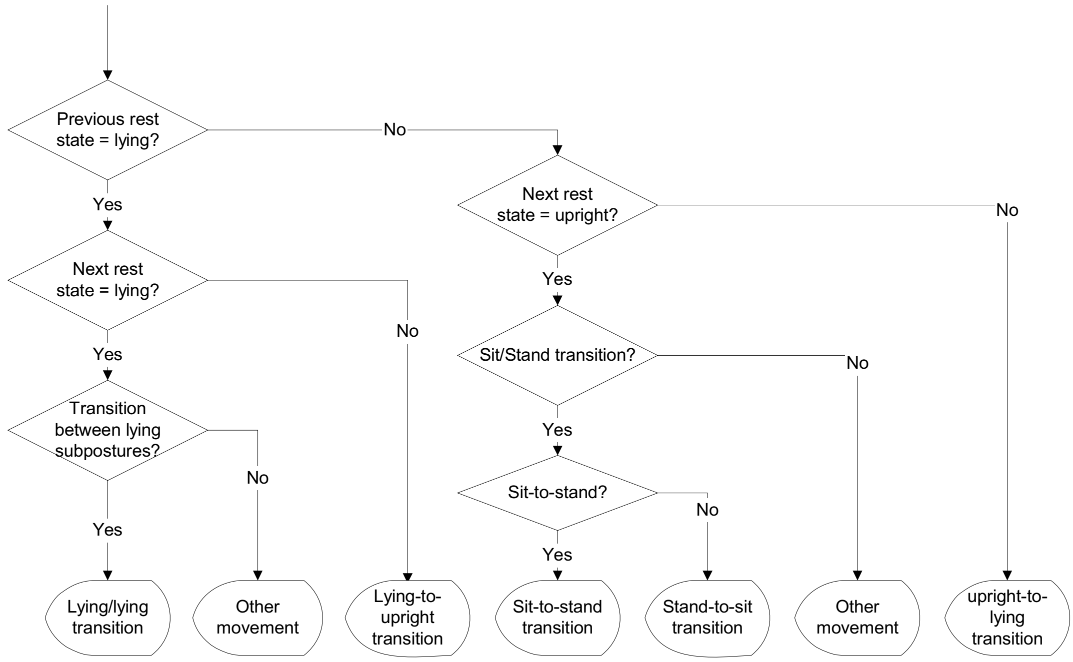


Figure 6.28: Flowchart for the classification of transitions.

Last state \ Next state	Lying back	Lying front	Lying left	Lying right	Not lying
Lying back	movement while lying on back	transition from lying back to lying front	transition from lying back to lying left side	transition from lying back to lying right side	transiton from lying to upright
Lying front	transition from lying front to lying back	movement while lying on front	transition from lying front to lying left side	transition from lying front to lying right side	transiton from lying to upright
Lying left	transition from lying left side to lying back	transition from lying left side to lying front	movement while lying on left side	transition from lying left to right side	transiton from lying to upright
Lying right	transition from lying right side to lying back	transition from lying right side to lying front	transition from lying right to left side	movement while lying on right side	transiton from lying to upright
Not lying	transition from upright to lying	transition from upright to lying	transition from upright to lying	transition from upright to lying	Not a lie-lie transition

Figure 6.29: All of the possible lie-to-lie transitions. The transition can simply be read from the table if the previous and next resting state postures are known.

6.9.2 Transitions Between Upright and Lying

Transitions between upright and lying can be determined by considering the postural orientation of the subject in the rest periods before and after the activity. These transitions can be further subclassified, for example, as a transition from sitting to lying supine if the subclassifications of the resting states are used rather than the main classifications of upright and lying.

6.9.3 Transitions between Lying Subpostures

Transitions between lying subpostures can be determined by identifying the postural orientation of the subject before and after the activity. If the postural orientations before and after the activity were lying but the subject was lying in two different positions, then the activity is classified as a transition between lying subpostures. Figure 6.29 lists all of the possible transitions.

6.9.4 Transitions Between Sitting and Standing

Introduction

The postural orientations of sitting and standing cannot necessarily be distinguished using only the resting state signal measured at the waist (refer to section 6.6.5). As a consequence, the presence of a sit/stand transition cannot be inferred by identification of the postural orientation in the adjacent periods of rest. This means that the transition, if it is to be classified, must be identified by means of characteristics of the transition signal itself, or deduced from a knowledge of the subject's routine.

In this study, methods of identifying sit-to-stand and stand-to-sit transitions from the TA signal characteristics were investigated.

The sit-to-stand transition was described in section 3.5. It is characterised by a lean forward, followed by a vertical rise, followed by a straightening up. The stand-to-sit transition is characterised by the same movements in the reverse order. The accelerations generated by each of these movements are illustrated in figure 6.30, which shows the signals from a TA unit attached at the front-right of the waist during each of the component movements of the transition, and the transition itself. The timing between the three components, and the magnitude of each component are individualistic parameters. However, it can be seen that both transitions generate a sinusoid-like shape on the z-axis. This is caused by the vertical acceleration and deceleration in the rise or descent phase. In the sit-to-stand transition, the peak precedes the trough, and in the stand-to-sit transition the order is reversed. The x- and y-axis signals increase slightly in value as the subject leans forward and they tilt away from the horizontal. They reduce in value again once the subject straightens. In the transitions this leads to a 'Λ' shape on the x- and y- axes as is seen in figures (b) and (d). In general, the initial and final steady state values of the x- and y- axis signals may differ, depending on the tilt angle of the subject while sitting, but the z-axis value both before and after the transition is close to 1 g.

In the classification framework, the sit-to-stand transition and the stand-to-sit transition are the last activities to be classified. Thus, only sit-to-stand transitions, stand-to-sit transitions and other unclassified movements such as bending down or reaching up are processed by this algorithm.

Three methods of identifying sit-to-stand and stand-to-sit transitions were investigated. The first method used a neural network that took the normalised raw signal as input. The second method used a neural network that was provided with a set of parameters that were deemed to be important. The third method used a rule-based expert system.

Experimental Procedure

One subject performed 1000 sit-to-stand transitions and 1000 stand-to-sit transitions. Three different chairs were used: a dining chair (used 334 times), a lounge chair (used 333 times) and an office chair (used 333 times). The subject began by standing in front of the dining chair. The subject then sat down into the dining chair and remained seated for 10 s. The subject then rose and remained standing for 5 s. The subject then walked approximately 20 paces to the lounge chair, and

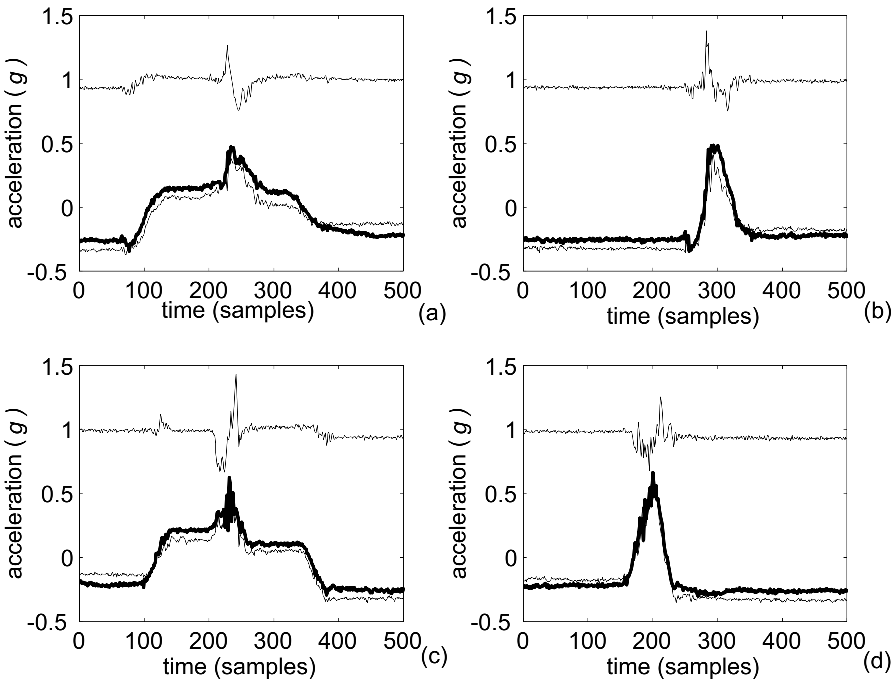


Figure 6.30: Sit-to-stand and stand-to-sit transition signals from a TA unit attached at the waist above the right anterior superior iliac spine. (a) The three stages of the sit-to-stand transition: lean forward (occurs at around 100 samples), rise (250 samples), straighten (350 samples). (b) A sit-to-stand transition performed by the same subject. (c) The three stages of the stand-to-sit transition: lean forward (100 samples), descent (250 samples), and straighten (350 samples). (d) A stand-to-sit transiton performed by the same subject. In each figure the z-axis signal is centered about 1 g, the x-axis signal is shown in bold, and the y-axis signal closely follows the x-axis signal.

stood in front of the lounge chair for 5 s. The subject then sat down into the lounge chair and remained seated for 10 s. The subject then stood for 5 s and then walked approximately 20 paces to the office chair. The subject stood in front of the office chair for 5 s, sat down for 10 s, stood for 5 s, walked approximately 20 paces to the dining chair, and then repeated this sequence of steps until 1000 sit-to-stand transitions had been completed. The data were collected in 1 hour sessions over a period of one week.

The same subject was then asked to stand for 5 s, walk approximately 20 paces, and then carry out some common movement other than the movements processed by the classifier such as bending down or reaching. The subject carried out 1000 such movements. The data were collected in 1 hour sessions over a period of three days.

These data were used to develop and train the neural network methods. They were also used to develop the expert system.

Data from the set of activities and rest that was described in section 6.5 were used to evaluate the performances of the methods. The data consisted of 93 stand-to-sit transitions, 103 sit-to-stand transitions and 10 short movements that were not transitions. The movements were made by a cohort of 26 normal, healthy subjects.

Data Analysis

The data were processed by the activity detection algorithm. Periods of walking and transitions between upright and lying were identified. Any periods of activity where the subject was not in an upright orientation both before and after the activity were rejected. The remaining periods of activity were processed to determine whether the subject was performing a transition between sitting and standing.

If the duration of the activity exceeded 5 s then the activity was classified as not being a transition. If the duration of the activity was less than 5 s then further processing was undertaken.

Three stages of testing were undertaken. In the first stage the data set of sit-to-stand transitions and stand-to-sit transitions was used and each of the methods was applied to distinguish between the two transitions. In the second stage the data containing activities that were not transitions was added and each of the three methods was applied to classify the movements as sit-to-stand transitions, stand-to-sit transitions or as other movement.

Finally, each of the three methods was evaluated using the set of activities taken from the cohort of 26 normal subjects.

Method 1: Neural network with raw signal input The first approach that was used was a neural network that accepted the raw signals as input. Each of the periods of activity to be tested was standardised to a 5 s period with the middle of the detected activity period at the centre of the standardised period. The signals were then downsampled by a factor of 3 (to a resulting sampling rate of 15 Hz) in order to reduce the number of inputs provided to the neural networks. This resulted in each test signal having a uniform length of 75 samples. The set of data were normalised such that the mean was 0 and the standard deviation was 1 across all of the training data as this improves the performance of the neural network [59].

Five different neural network systems were developed and tested. All of the networks were backpropagation networks and used steepest descent training with a momentum term to train the networks.

The first system consisted of a 3-layer backpropagation network with 231 inputs, 24 hidden units and 2 outputs. The inputs consisted of 75 normalised acceleration inputs, and the signal mean and standard deviation before normalisation, for each of the x-, y-, and z-axis signals. The two outputs were "sit-to-stand transition detected" and "stand-to-sit transition detected". A "winner takes all" function was applied to determine the final result. This network was trained with 676 randomly selected examples of sit-to-stand transitions and stand-to-sit transitions. The network was then tested on a set of 36 different transitions.

The network was then extended by adding a third output for "no transition". The network was trained with 957 randomly selected examples of sit-to-stand transitions, stand-to-sit transitions, and other movements. The trained weights from the two-output network were used as the initial training weights. The network was tested on the test set of 36 transitions and 36 other activities.

The second network was identical to the first, but the signals from the x-, y- and z-axes were rotated about the z-axis so that they lined up with the antero-posterior, medio-lateral and vertical axes of the subject. This rotation was done before the signals were downsampled and normalised. The same procedure as above was followed for training and testing the network.

The third network consisted of a 3-layer backpropagation network with 77 input neurons, a hidden layer containing 12 neurons and 2 output neurons. The inputs to the network were 75 samples of the normalised magnitude vector, ρ, and its signal mean and standard deviation. This network was trained with the data set of 676 transitions and tested on the data set of 36 transitions. It was then extended to include a third output and the new network was trained with the data set of 957 activities and tested with the set of 72 activities.

The fourth network was identical to the third except that the input signal was the z-axis signal.

The fifth system consisted of three networks identical to the third network. Each network used one of the three x-, y- and z-axis signals as input. The same procedure was followed as for the third network, except that rather than a "winner takes all" algorithm being applied to each network, the output values for each output from each network were summed together and then a "winner takes all" algorithm was applied to determine the final result.

Method 2: Neural network with parameters as inputs A 3-layer back-propagation neural network was developed with 21 inputs, 7 hidden neurons and 2 outputs. The seven input parameters were:

1. maximum value;
2. sample at which the maximum occurs;
3. minimum value;
4. sample at which the minimum occurs;
5. r.m.s.;
6. mean; and
7. standard deviation.

The network was trained with the data set of 676 transitions and tested on the data set of 36 transitions. It was then extended to include a third output and the new network was trained with the data set of 957 activities and tested with the set of 72 activities.

Method 3: Expert system The expert system used a rule-based pattern matching technique that was developed from the nature of the transition signals. The signals from the TA were rotated so that the x-, y- and z-axes corresponded to the antero-posterior, medio-lateral and vertical axes of the subject respectively. Two rule-based systems were developed: one for the x-axis, and the other for the z-axis. The y-axis was omitted because the three basic components of the transitions are in the forward-back and up-down directions, and there is not a significant left-right component.

The rotated x-axis signal was compared to the 'Λ' shape of the ideal sit/stand transition. If the signal was in this form then this part of the algorithm classified the activity as a sit/stand transition. This was achieved in the following manner. The rotated x-axis signal was modelled by a smooth spline. Turning points in the spline were found and peaks and troughs were identified. If there were too many distinct peaks (global maxima) in the signal (threshold was set to 15 after preliminary testing) then the signal was classified as not being a sit/stand transition by this part of the algorithm. Otherwise, the algorithm then tested to see whether the shape of the x-axis signal matched the expected shape. If it did not then it was classified as not being a sit/stand transition by this part of the algorithm. Otherwise, it was classified as being a sit/stand transition by this part of the algorithm.

Next, the x-axis tilt angle before the activity was compared to the x-axis tilt angle after the activity. If the change in angle exceeded a threshold (here set to $20°$ after preliminary testing) then this second part of the algorithm classified the movement as a sit/stand transition. If the starting tilt angle was less than the finishing tilt angle, it was regarded as evidence in favour of a stand-to-sit transition. If the starting tilt angle was greater than the finishing tilt angle, it was regarded evidence in favour of a sit-to-stand transition.

The z-axis signal was similarly modelled by a smooth spline and global peaks and troughs (as opposed to local inflexions) were identified in the signal. If there were too many distinct peaks (threshold = 15) then the signal was classified as not being a sit/stand transition by this part of the algorithm. Otherwise, the biggest peaks and the biggest troughs were identified. If there was one large peak and one large trough, and if the peak preceded the trough then the signal was classified as a sit-to-stand transition. If the trough preceded the peak it was classified as a stand-to-sit transition. If there was a sequence of peak-trough-peak, or trough-peak-trough then the signal was classified as a sit/stand transition but the algorithm could not tell which one.

The results of these algorithms were collated and another algorithm used to decide whether the activity was a sit-to-stand transition, a stand-to-sit transition or neither. The algorithm began with the three parameters:

$$x = \begin{cases} 1, & \text{if sit/stand transition} \\ 0, & \text{otherwise} \end{cases} \tag{6.8}$$

$$z = \begin{cases} 1, & \text{if sit-to-stand transition} \\ 2, & \text{if stand-to-sit transition} \\ 0, & \text{otherwise} \end{cases} \tag{6.9}$$

$$t = \begin{cases} 1, & \Delta \text{ tilt angle} < -20° \\ 2, & \Delta \text{ tilt angle} > 20° \\ 0, & \text{otherwise} \end{cases} \tag{6.10}$$

where x was the result of processing of the x-axis signal, z was the result of processing of the z-axis signal, and t was the result of processing of the tilt angle.

These parameters were combined according to the following rules:

1. $transition := x + signum(z) \ + signum\,(t)$
2. $std = \begin{cases} (z=1)+(t=1) & \text{if } transition > 0 \\ 0 & otherwise \end{cases}$
3. $sit = \begin{cases} (z=2)+(t=2) & \text{if } transition > 0 \\ 0 & otherwise \end{cases}$
4. if $transition >\ 0$ then the movement was classified as a sit/stand transition.
5. if $sit > std$ then the movement was classified as a stand-to-sit transition.
6. if $std > sit$ then the movement was classified as a sit-to-stand transition.
7. if $sit = std$ then the movement was classified as indeterminate.

Results

Method 1: Neural network with raw signal input The first system in which all data from all three axes was provided to a single, large neural network gave the best performance. When this network with two outputs was trained and tested on the data set of 36 sit/stand transitions made by 1 subject it made 34 correct classifications and 2 incorrect classifications. When the network with three outputs was trained it correctly classified 28 of the 36 test transitions (78%) but only 13 of the 36 other activities (33%). One stand-to-sit transition was classified as a sit-to-stand transition. The other five incorrectly classified transitions were classified as non-transitions.

		total activities tested	number correctly classified		
			net1	net2	expert system
test data set 1	sit	18	12	18	15
	stand	18	16	18	15
	other	36	13	23	10
	total	72	41 (56.9%)	59 (81.9%)	40 (55.6%)
test data set 2	sit	93	48	90	87
	stand	103	50	9	101
	other	10	3	0	5
	total	206	101 (49.0%)	99 (48.1%)	193 (93.7%)

Table 6.9: Results of the three sit/stand transition classification methods when applied to a data set of 72 activities from 1 subject (test data set 1), and to a data set of 206 activities from 26 subjects (test data set 2).

When this network was tested on the data set of movements made by the 26 normal, healthy subjects, it correctly classified 49.03% of the activities.

Method 2: Neural network with parameters as inputs The parameterised neural network was trained on the same data set as the neural network that accepted the raw signal as input. When this network with two outputs was trained and tested on the data set of 36 sit/stand transitions made by 1 subject it made 35 correct classifications and 1 incorrect classifications. When the network with three outputs was trained it correctly classified all of the 36 test transitions (100%) and 23 of the 36 other activities (63.9%).

When this network was tested on the data set of movements made by the 26 normal, healthy subjects, it correctly classified 48.1% of the activities.

Method 3: Expert system When the expert system was tested on the data set of 36 sit/stand transitions and 36 other movements made by 1 subject it correctly classified 15 of the 18 sit-to-stand transitions (83.3%), and 15 of the stand-to-sit transitions, but only 10 of the 36 other movements (27.8%). When it was tested on the data set of movements made by the 26 normal, healthy subjects, it correctly classified 93.7% of the activities. Two sit-to-stand transitions (1.9%) were incorrectly classified as stand-to-sit transitions. Six stand-to-sit transitions (6.5%) were identified as sit/stand transitions but the transition could not be sub-classified as sit-to-stand or stand-to-sit.

The results from the three different classification methods are summarised in table 6.9.

Discussion

The neural networks were trained on a data set taken from a single subject. When tested on data from this same subject, the best performance was achieved by the parameterised neural network (81.9% correct classification). The other neural network and the expert system gave similar performances (56.9% and 55.6% respectively). However, when these methods were applied to data from the 26 different subjects the parameterised network performed poorly (48.1%), classifying almost every movement as a stand-to-sit transition and the first network gave a similar performance (49.0%) although it identified about half of the activities in each category, whereas the expert system performed very well (93.7%), identifying almost all of the transitions correctly, and half of the other movements.

These results suggest that the neural networks identified features that were specific to the one subject on whom they were trained, rather than identifying general features of sit-to-stand and stand-to-sit transitions. This resulted in good classification results for this one subject, but much poorer results when applied to the activities of other subjects.

On the other hand, the expert system method performed only moderately on the data from the single subject. It can be seen from table 6.9 that the main difference in performance between the parameterised network and the expert system was in the classification of other movements. The expert system classified almost all of the transitions correctly, but only correctly classified 25% of the other movements, compared to 63.9% for the parameterised neural network. Most of the movements performed by the subject were bending and reaching movements that were chosen because of their similarity in form to the transitions. Movements such as wiggling of the hips or turning around result in a very different signal trace and are relatively easily identified as not being a transition. In the data from the 26 other subjects, the other movements were random movements made by the subjects and the expert system performed better here, correctly identifying half of them as other movement.

The main disadvantage to using the neural network approach is that the neural networks require a large amount of training data and take a long time to train. In this study a training data set from a single subject was used because large amounts of data from a range of different subjects was not available at the time. The expert system has the advantage that only a small quantity of training data is required. On the other hand, once trained, neural networks provide very rapid classification.

The first neural network approach has a second limitation in that all of the input signals need to be the same length but not all transitions are of the same duration.

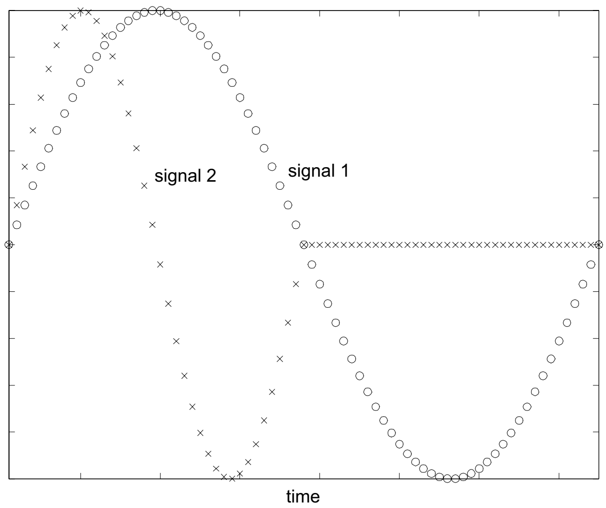


Figure 6.31: Example showing the same activity accomplished in different amounts of time. Signal 1 is one period of a sine wave. Signal 2 is identical to signal 1, except that it is completed in half the time. The marked points indicate the values provided to the neural network at each point in time. It can be seen that these two signals result in very different sets of input values.

This means that two instances of the same transition may result in very different values for the normalised signal input parameters (figure 6.31), which may increase the difficulty in training the network.

The 5 s duration limit on the neural network input data was introduced to the algorithm to prevent unnecessary processing time being spent on movements that could not be simple transitions. The 5 s threshold was chosen for this subject cohort because all subjects could complete a sit-to-stand or a stand-to-sit transition in 1–3 s. The duration threshold would need to be extended or omitted before this algorithm was applied to data from an elderly or disabled person who took longer to perform transitions.

It may be possible to increase the accuracy of these classifications if the activities and resting states before and after the activity can be identified. For example, if the subject walks, rests (standing), an upright/upright movement occurs, rests (standing), and walks, it could be deduced that the movement was not a transition. On the other hand, if the subject sits, an upright/upright movement occurs, a resting period occurs, and then the subject walks, it can be deduced that the subject performed a sit-to-stand transition and then stood before walking. Similar deductions can be made for other scenarios that may occur.

Conclusion

Three different systems were used to classify sit-to-stand transitions, stand-to-sit transitions and non-transitional movement. These were a neural network that used TA signals as input, a neural network that used parameterised data from the TA signals as input, and a rule-based expert system. The parameterised neural network performed best on test data taken from the same subject from which it was trained, with an accuracy of 81.9%. The expert system performed best on a second data set taken from 26 normal subjects with an accuracy of 93.7%. The expert system has the advantage that no training is required.

If an activity is known to be a transition between sitting and standing, it can be classified with a high degree of accuracy. The classification accuracy is reduced by the introduction of movements such as bending over and straightening which have a signal pattern similar to that of a transition.

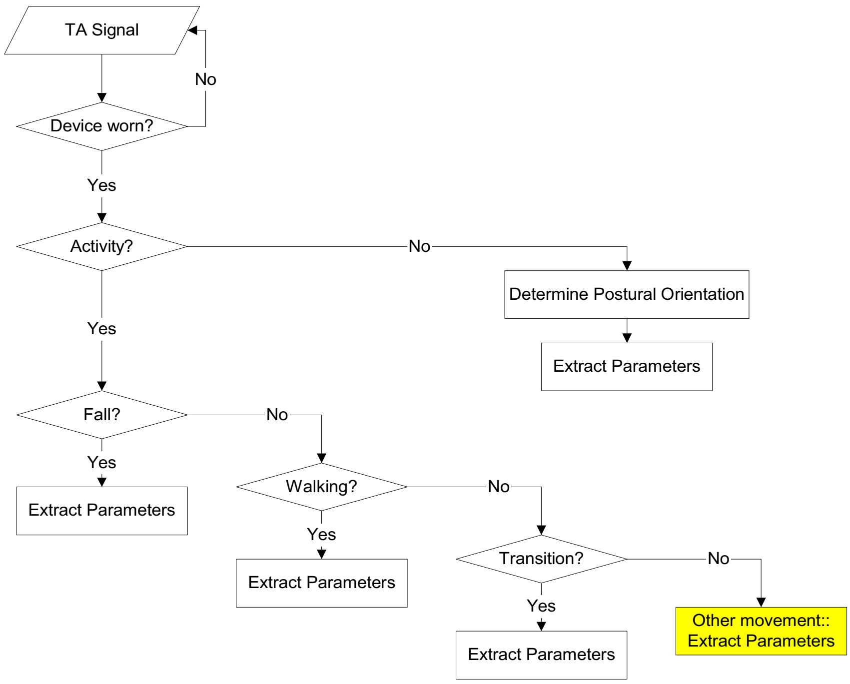
Future work should involve the collection of data from a cohort of free-living subjects at home. These data should be used to train the second neural network in order to evaluate its performance when trained with data from multiple subjects, and to evaluate its performance in identifying transitions in the same subject over time. A second stage of future work should involve developing a heuristic overlay for this algorithm that deduces the nature of the activity given some knowledge of the activities and postural orientations immediately preceding and following the activity.

6.9.5 Transitions—Parameter Extraction

Once a transition between postural orientations has been identified, parameters of interest that can be recorded from the TA are

- the time taken for the transition; and
- the amount of movement as measured by the SMA.

6.10 Classifying Other Activities



Classification of other activities.

There is scope in the classifier framework for algorithms to be developed and added to identify and parameterize other activities. However, given the virtually infinite domain of activities that can be carried out by a free-living subject there will always be some unclassified activities.

The parameters of interest that can be recorded for these activities are

- the time taken for the movement;
- the amount of movement as measured by the SMA; and
- the overall amount of time spent each day in unclassified activities.

In addition, the signal pattern of the unclassified activity can be stored and compared to the signal patterns of other unclassified activities. Similar activities can be grouped together. The occurrence of different activity groups can be tracked over time. Suggested methods for achieving this are discussed in section 9.5.

6.11 The Complete Classifier

The data analysis framework is based on examining windows of signal, and classifying each window as either activity or rest. Once a complete activity signal is obtained (a period of rest following the activity is identified) then the activity is classified according to the binary ripple-down system that has been described. Periods of rest can be processed as soon as they are first identified, and the classification updated as the period of rest continues, or they can be stored and processed at the completion of the period of rest. The complete classifier is shown in figure 6.32.

6.12 Discussion

The aim of this chapter was to determine methods for interpreting the TA signal and to ascertain what could, and could not be identified by a single waist mounted TA. A waist mounted TA has obvious limitations when compared to systems with multiple instruments. For example, it is not as effective in distinguishing between sitting and standing, nor at identifying temporal parameters of gait than a system that includes accelerometers attached to the thigh, but it has the advantage of being easier to use for the subject and hence more practical for unsupervised monitoring.

Even though the single waist mounted TA has limitations when compared to systems with multiple accelerometers, the studies described in this chapter have demonstrated that such a device can be used to collect a large amount of valuable information on a subject's movement, and in a way that is practical and appropriate for continuous, unsupervised monitoring of free-living subjects. Activity and rest can be distinguished with a high degree of accuracy. Upright and lying postures can be distinguished with certainty, gait can be detected with confidence and the step rate reliably identified. Individual steps can be identified within the walking signal - the template matching algorithm detected 4020 walking steps with an overall sensitivity of 90.5% and specificity of 99.0%.

The modular design of the overall classification framework means that the performance of each algorithm can be individually evaluated. New or improved algorithms can easily be incorporated into the classification structure.

All of the algorithms were designed to be suitable for close to real-time data processing (within approximately 10 s of data being received). The fall detection algorithm continuously monitors incoming activities for high acceleration peaks, which initiate the rest of the fall detection algorithm. The other activity identification algorithms were designed for processing to take place once the activity is

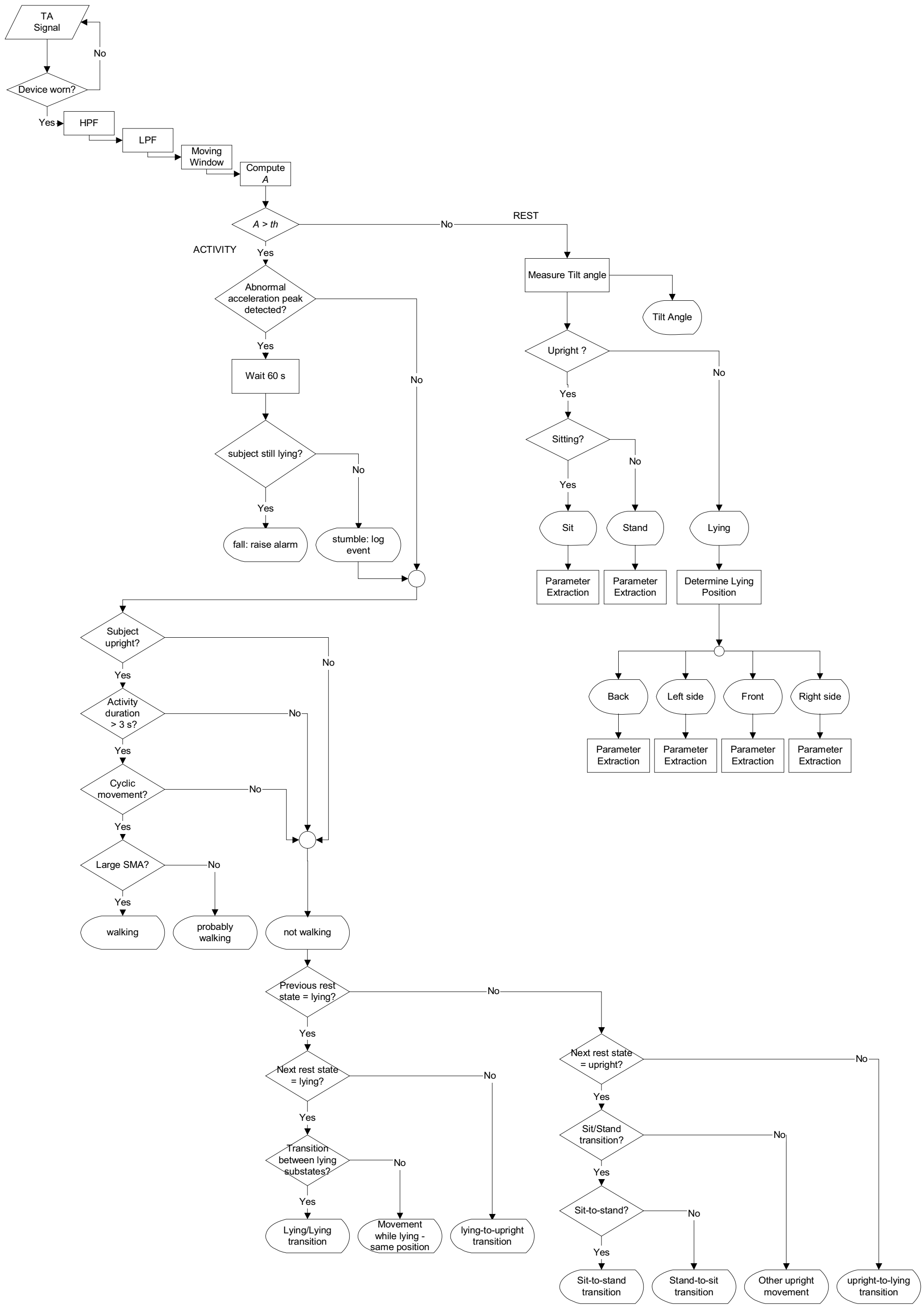


Figure 6.32: The complete classifier

completed. However, if the activity continues for longer than a threshold value (approximately $5-10\,\mathrm{s}$, depending on the subject being monitored) then the hypothesis that the movement is a transition can be rejected and the part of the activity that has already occurred can be tested to determine whether or not the subject is walking. Resting states can be classified immediately, and the classification checked periodically during the rest period as new data is received.

The studies in this chapter have demonstrated that important parameters, such as activity duration, energy expenditure, tilt angle, step rate and peak acceleration, can be measured using a single waist-mounted TA. In addition to parameter tracking, the data from the TA can be used to develop a "behavioural map" for the subject. If the times at which each movement occurs are logged then a picture of the subject's daily activities can be built up. This can be developed into a daily activity template that can be tracked longitudinally to detect behavioural changes that may be indicative of changes in functional health status [43].

6.13 Chapter Conclusion

This chapter has presented a method for interpreting the signals from a waist-mounted TA in terms of human movement. A framework for classification based around a hierachical binary tree with "ripple down" rules was introduced. This enabled a classification of the acceleration signals into movements performed by the subject. The framework was designed to be suitable for real time use.

An implementation of the framework specific to the needs of unsupervised monitoring of free-living subjects at home was presented. This focussed on the identification of important basic movements, including lying, sitting, standing, walking and falls. A suite of algorithms was developed for each stage of the processing. These algorithms were evaluated using data taken from normal subjects performing directed movements in a laboratory setting.

The root mean square of the signal was used to determine whether or not the TA unit was being worn by the subject. This was tested with data taken from 26 normal subjects who stood, sat and lay as still as possible while wearing the TA unit. These data were compared to data from periods in which the TA unit was not being worn. There was a statistically significant difference between the root mean square values of the signals when the TA unit was being worn and when it was not being worn ($p < 0.02$).

An algorithm was developed to distinguish between periods of activity and periods of rest in the signal. The algorithm was developed using data from 13 normal subjects, and was tested using data from a further 13 normal subjects. The algorithm used three codependent parameters—median filter length, n, window width, w, and energy threshold level, th. When the algorithm was applied to the control group, optimal parameters were determined to be $n = 13$ samples, $w = 0.8\,\mathrm{s}$, and $th = 0.1575\ g$. Use of the algorithm with these parameters gave a true positive rate of 99% and a false positive rate of 6% in the test group when distinguishing between periods of activity and periods of rest.

Algorithms were developed to distinguish between resting states. Upright and lying were distinguished with 100% accuracy by means of the vertical tilt angle. Lying subpostures were determined by comparing the mean acceleration vectors of the lying state to nominal values for each subposture, derived from the model developed in section 5.4.3. This algorithm subclassified 92 instances of 4 lying subpostures with 99% accuracy. In a preliminary study a rule based classifier successfully distinguished between sitting and standing with 97% accuracy.

A two stage algorithm was developed for the detection of falls. The algorithm firstly identified abnormally large accelerations in the signal. When a large acceleration was detected then the postural orientation of the subjects was monitored to determine whether or not the subject had fallen. Several variations on the algorithm were evaluated on a data set consisting of 8 falls and 8 stumbles performed by two normal subjects. The algorithm parameters were optimised so that the algorithm detected all of the falls and stumbles and generated no false positives. This was then tested on a new data set of 8 falls performed by two normal subjects, where it detected 7 of the 8 fall events.

Three approaches to the detection and assessment of walking were developed and evaluated. Firstly, an algorithm based on the Fourier transform was developed. This algorithm was evaluated on a set of 156 periods of walking performed by 26 normal subjects. The highest detection rates were obtained when the z-axis (vertical) acceleration alone was used. This algorithm determined the average step rate for the period of gait. However, it was unable to measure the step-by-step period, nor was is suitable for irregular gait. A second method was developed in which a template in a sliding window was applied to the signal and periods in the signal that matched the template were identified as steps. This method was tested on data taken from 8 normal subjects each walking at 5 different speeds. The algorithm detected each step with a sensitivity of 90.5% and a specificity of 99%. This algorithm allowed the step-by-step period and variability to be measured. The third method developed was a rule based system designed to efficiently detect periods of walking activity. The Fourier based method and the template matching method were included in this algorithm to determine whether or not the movement that was being performed was cyclic. Other rules assessed the postural orientation of the subject and the duration of the period of activity. This system was tested on periods of walking taken from 26 normal subjects. It identified 90.9% of the periods of walking as "definitely walking", and the remaining 9.1% as "probably walking". All non-walking activies were correctly classified as "not walking".

Postural transitions were identified in a series of algorithms. Transitions between upright and lying states were identified with 100% accuracy. Transitions between sitting and standing were identified by an expert system with 93.7% accuracy. Several backpropagation-based neural networks were also used to identify transitions between sitting and standing, but these performed with lower accuracy rates (49% on the same data set). The training data for the neural networks was limited and the results may be improved by training with more data from a range of different subjects.

Once a movement was identified, movement-specific parameters could be extracted from the signal. These parameters included tilt angle, activity duration, walking speed, postural sway and energy expenditure as measured by SMA. Many of these parameters, such as sit-to-stand transition time and walking speed, have known clinical relevance as indicators of functional status. Others provide further information on the movement that may prove clinically useful when tracked longitudinally. All of these parameters were able to be directly and simply extracted from the signal once the movement was identified.

The next chapter describes the design of experimental studies to use, and evaluate the use of, the TA system in unsupervised settings in the monitoring of free-living subjects at home.

Chapter 7

Experimental Design

7.1 Overview

In chapter 6 a framework for the classification of movements from the TA signal was presented. A classification algorithm that identified important activities and resting postures was developed and evaluated using data obtained from a cohort of normal, healthy subjects under controlled conditions. Once a movement was identified, a set of parameters deemed to have potential clinical significance was extracted from the signal. These included measurements of sit-to-stand transition time and walking step rate. The system was developed for the purpose of unsupervised monitoring of human movement in order to identify adverse events and changes in functional status.

In order to evaluate the performance of the TA monitoring system (including the TA unit, the classification algorithm and parameter extraction techniques) for unsupervised monitoring of free-living subjects, a series of experimental studies were conducted in laboratory and home environments, under supervised and unsupervised conditions. This chapter describes the experimental designs of these studies.

A methodology for use of the TA system in free-living conditions was developed. In this methodology there were two stages to the assessment of movement. Each day the subject was required to carry out a short routine of basic daily movements. The movements were identified in the signal and parameters were extracted and tracked longitudinally. The subject then continued to wear the TA unit for the remainder of the day. During this period of free movement, the subject was monitored in order to identify adverse events such as falls. General parameters of movement, such as metabolic energy expenditure (as measured by the signal magnitude area, SMA) and time spent in activity were recorded and tracked longitudinally.

The two stages of monitoring were evaluated separately. The procedure for monitoring directed movement was tested in both laboratory and home settings, under supervised and unsupervised conditions. The procedure for monitoring free movement was tested in a home setting under supervised and unsupervised conditions. The studies in which data were collected from directed movements performed in a supervised laboratory setting were described in chapter 6. In this chapter the designs of the other studies are described. The results of the studies are presented and discussed in chapter 8.

7.2 Development of a Methodology for Unsupervised Home Monitoring with a Triaxial Accelerometer

The laboratory studies that were described in chapter 6 demonstrated the feasibility of using a single waist-mounted TA to

- identify adverse events such as falls; and
- longitudinally track parameters that are sensitive to changes in health or functional status.

However, before the classification framework could be applied to the processing of signals from unsupervised free-living subjects there were a number of issues that needed to be addressed:

1. The subject may attach the TA unit in a different position on different days. A daily calibration procedure was required to identify the TA placement so that postural orientations could be correctly identified.

2. There are limitations to what can be achieved with only a single TA unit. For example, sitting and standing postures cannot be distinguished with certainty. In free movement, basic daily activities and postures can be identified with a high degree of probability, but not with certainty. However, for longitudinal tracking of parameters of movement it is necessary that activities and postural orientations be correctly identified.

3. It is also necessary for longitudinal tracking of parameters of movement that the activities are repeated in the same manner each day. For example, the sit-to-stand durations of the same subject rising from a low-seated lounge chair and from an upright dining chair are different as the movements are

different. Sit-to-stand transitions carried out by the same subject can only be monitored for longitudinal changes if carried out in the same manner from the same chair. The same applies to all other movements.

A methodology that addressed each of these issues was developed for assessment of movement using the TA in a free-living context. In this, the monitoring was accomplished in two stages. The first stage involved monitoring of movement through a directed routine. The second stage involved monitoring of free movement.

The purpose of the first stage was to identify the placement of the device on the waist, and to allow clinically significant parameters to be tracked from day-to-day by repeating a series of known movements on a daily basis. This required the subject to carry out a short sequence of movements each morning while wearing the TA. The sequence took approximately five minutes to complete and included basic daily activities and postures such as standing, sitting, lying, transitions between sitting and standing and between standing and lying, and walking. If the sequence were to be used for monitoring patients with a specific condition it could be adapted to include activities that provide useful information specific to the condition of the subject. To ensure that the movements are carried out in the same manner each time, it is important that the same routine be carried out each time, that the activities occur in the same order, and that the same furniture (chair and bed) are used on each occasion.

The quiet standing and lying components of the routine allow the placement of the TA device to be determined as both the postural orientation and the TA signal are known (refer to section 5.4). Since a known sequence of movements is performed in the routine, these movements can be identified more reliably than in free movement. If the same routine is then repeated on a daily basis, the extracted parameters can be tracked over time.

After completing the routine of directed movement, the subject was required to continue wearing the TA device for the rest of the day. The primary purpose of the second stage of monitoring was to identify any adverse events that may occur. This phase was also used to track other relevant parameters such as hourly and daily SMA, and the amount of time spent in rest and activity.

This two-stage approach to monitoring free-living subjects satisfies all of the monitoring requirements listed above. It allows parameters to be extracted from known movements that are repeated in the same sequence and manner each day, which allows them to be tracked longitudinally. It provides a simple method for identifying the placement of the TA unit on the waist of the subject. It also allows the subject to be monitored continuously for adverse events and for the collection of general parameters of movement, such as energy expenditure. Moreover, use of the directed routine greatly reduces the amount of data processing and information storage that is required. All of the important movements are carried out every day within a period of only a few minutes. Outside of the directed routine period, only the general parameters of movement and information pertaining to adverse events need to be calculated and stored.

7.3 Stages of Experimental Processing

Before the system could be used in an unsupervised home setting its performance needed to be tested and validated in controlled conditions.

There are four basic stages to testing and validating a system for unsupervised monitoring of a given subject group. These stages are:

1. **testing in a supervised laboratory environment**. In this setting, the activities undertaken by the subject can be carefully controlled and independently measured.
2. **testing in an unsupervised laboratory environment**. The activities undertaken by the subject can be carefully controlled, but the manner in which the subject undertakes them cannot be controlled.
3. **testing in a supervised home environment**. The activities undertaken by the subject are those normally undertaken by the subject, and cannot be controlled by the investigator, but the manner of carrying out the activities, including the manner of wearing the ambulatory monitoring device, are supervised by the investigator.
4. **testing in an unsupervised home environment**. Here, neither activities nor the manner of carrying out those activities is under the control or observation of the investigator. An independent measure, for example, video or a diary, is needed to provide a reference against which the accelerometer measurements can be validated.

This four-stage process needs to be undertaken first using normal subjects. If there is a particular cohort of interest, the tests can then repeated using the target subject group.

There is a natural ordering of activities, which is shown in figure 7.1. Each successive activity is more complicated than, and dependent upon, the preceding

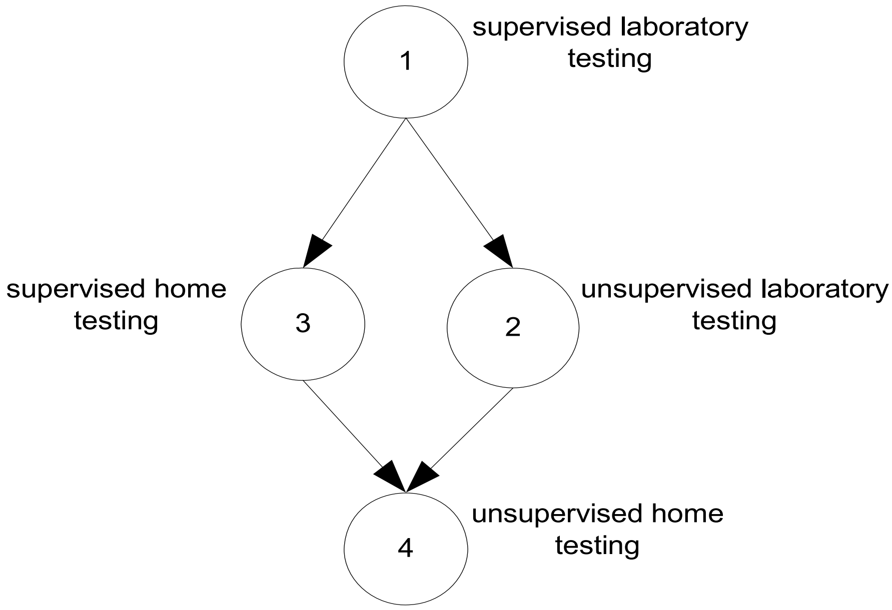


Figure 7.1: The flow of activities in testing and evaluation. 1. Supervised laboratory testing; 2. unsupervised laboratory testing; 3. supervised home testing; 4. unsupervised home testing. Each activity is dependent upon the activities higher up in the tree.

activities. Steps 2 and 3 can only be carried out once step 1 is complete, and step 4 is dependent on the completion of the first three steps.

In the current work, both directed and free movement were studied in different settings. Figure 7.2 shows the studies that were undertaken in the current work. The routine of directed movement was evaluated in all four settings (in supervised and unsupervised studies performed in the laboratory and in the home) using cohorts of normal subjects.Performance of the system in monitoring free movement was only evaluated in the home environment. This was because movements performed in a laboratory setting could not adequately reflect movements performed in a home setting, and so were of little value in establishing patterns of movement in a home setting. In the current work, studies are referred to by a two character code, e.g. '3D'. The first character is a number between 1 and 4, corresponding to the type of study—supervised or unsupervised, laboratory or home—the numbers correspond to those shown in figure 7.1. The second character is either 'D' for directed movement, or 'F' for free movement.

The supervised and unsupervised laboratory studies of directed movement were conducted using different cohorts of normal subjects. The supervised home studies of directed and free movements were performed by the same subject in the same

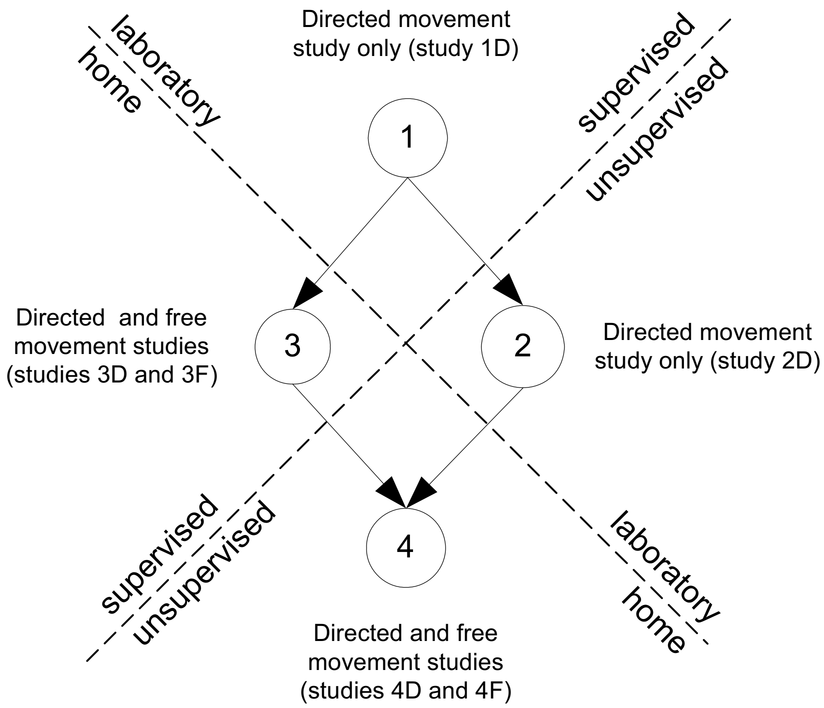
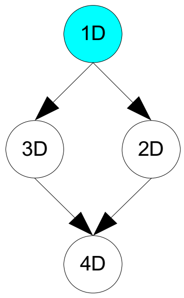


Figure 7.2: Studies undertaken in the current work. The codes 'D' and 'F' are used to represent the studies of directed and free movement, respectively. The studies were 1D: supervised laboratory study of directed movement, 2D: unsupervised laboratory study of directed movement, 3D: supervised home study of directed movement, 3F: supervised home study of free movement, 4D: unsupervised home study of directed movement, and 4F: unsupervised home study of free movement.

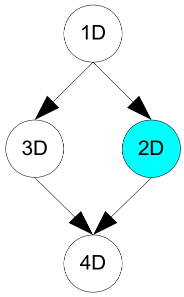
home. The unsupervised home studies of directed and free movements were conducted in a single study using a cohort of healthy elderly subjects.

7.4 Experimental Procedure for the Supervised Laboratory Studies of Directed Movement (study 1D)



The supervised laboratory studies were conducted in the Biomedical Systems Laboratory and in the School of Electrical Engineering and Telecommunications at the University of New South Wales. Cohorts of normal subjects carried out carefully controlled programmes of routine daily activities while being observed by an investigator who directed each step of the testing. These studies were designed to allow the collection of high-quality data from known movements. These data were used to facilitate understanding of the TA signals, and to develop the algorithms for automated real-time interpretation of the signals. All of these experiments have been described in the preceding chapters.

7.5 Experimental Procedure for the Unsupervised Laboratory Study of Directed Movement (study 2D)



Introduction

The next phase of the work involved carrying out a directed routine in an unsupervised setting. Subjects carried out a specific programme of routine daily activities but movements were neither observed nor controlled by an investigator.

The aims of this study were

1. to collect data from subjects performing in an unsupervised, controlled environment;
2. to determine normal values and ranges for the parameters extracted by the classification system; and
3. to compare these values to the values obtained from the supervised laboratory studies.

This study differed from the supervised laboratory study of directed movement in two ways. Firstly, the subjects were not directed by an investigator and, secondly, the same subjects repeated the routine on different days. This allowed the way that the subjects performed the routine without supervision to be measured in a controlled testing environment. The repetition of the test by the subjects allowed the data to be examined for intra- and inter-subject variability.

Setting

The unsupervised laboratory study of directed movement was conducted in the offices of the Centre for Health Informatics (CHI) at the University of New South

Wales. A TA system was set up in the central, open plan design, office. Subjects carried out the test routine in this office space.

Equipment

The system employed in the study consisted of a dedicated personal computer running the Microsoft Windows 98 operating system, a TA unit and a receiver board. A graphical user interface (GUI) was developed for the study to guide the subject through the routine. At the commencement of each test, the subject was required to log on to the system. The first instruction was then presented to the subject on the GUI. Once this task was completed, the next instruction was displayed on the GUI, and so on until the routine was completed.

The wording of the instructions was developed by means of an iterative process prior to the study in which the set of instructions was shown to the subjects, who provided feedback. The instructions were modified on the basis of the feedback and the process repeated until all of the subjects found all of the instructions very clear.

The final set of instructions that were given during the test procedure were:

1. Press the button on the monitoring device when you are standing up and ready to start the testing.

2. Please remain standing for the next 30 seconds.

3. Please sit down.

4. Once you are seated, press the button on the monitoring device.

5. Please stay seated.

6. Now stand up again.

7. Once you are standing, press the button on the monitoring device.

8. Please stay standing.

9. Now walk around the office. Follow the same route that you always take during this testing programme.

10. Once you have finished and are standing beside your bed, press the button on the monitoring device.

11. Please stay standing.

12. Now lie down.
13. Once you are lying down, press the button on the monitoring device.
14. Please stay lying.
15. Now stand up again.
16. Once you are standing, press the button on the monitoring device.
17. Please stay standing.
18. That completes these tests for today. Thank you.

Figure 7.3 shows the graphical user interface for instructions 1 and 4.

The computer was configured so that when it was powered up, the TA monitoring programme automatically started up. The system was designed to run continuously, but in the event of a "crash" the user needed only to reboot the machine to fix the problem.

Subjects

The purpose and methodology of the study were explained to the CHI staff. Staff who volunteered to participate in the study gave their informed consent. The gender and age of each subject were recorded. All subjects were healthy and had no functional disability.

Experimental Procedure

The study ran for a four week period. Each subject was asked to carry out the predetermined routine of basic daily activities at least once for each day that they were in the office. The routine could be carried out at any time during the day, and it did not need to be carried out at the same time each day. This was so that participation in the study would not interfere with the subjects' work programmes.

When a subject wished to carry out the routine, he or she selected one of four rechargeable AA batteries and inserted it into the TA unit, which was then attached to the waist above the right anterior superior iliac spine. The subject then logged into the system. The login procedure was used to identify the subject.

The subject was asked to press the button after completing each activity (steps 4, 7, 10, 13 and 16). The system waited until the subject pressed the button before moving on to the next instruction. This ensured that the speed at which the test

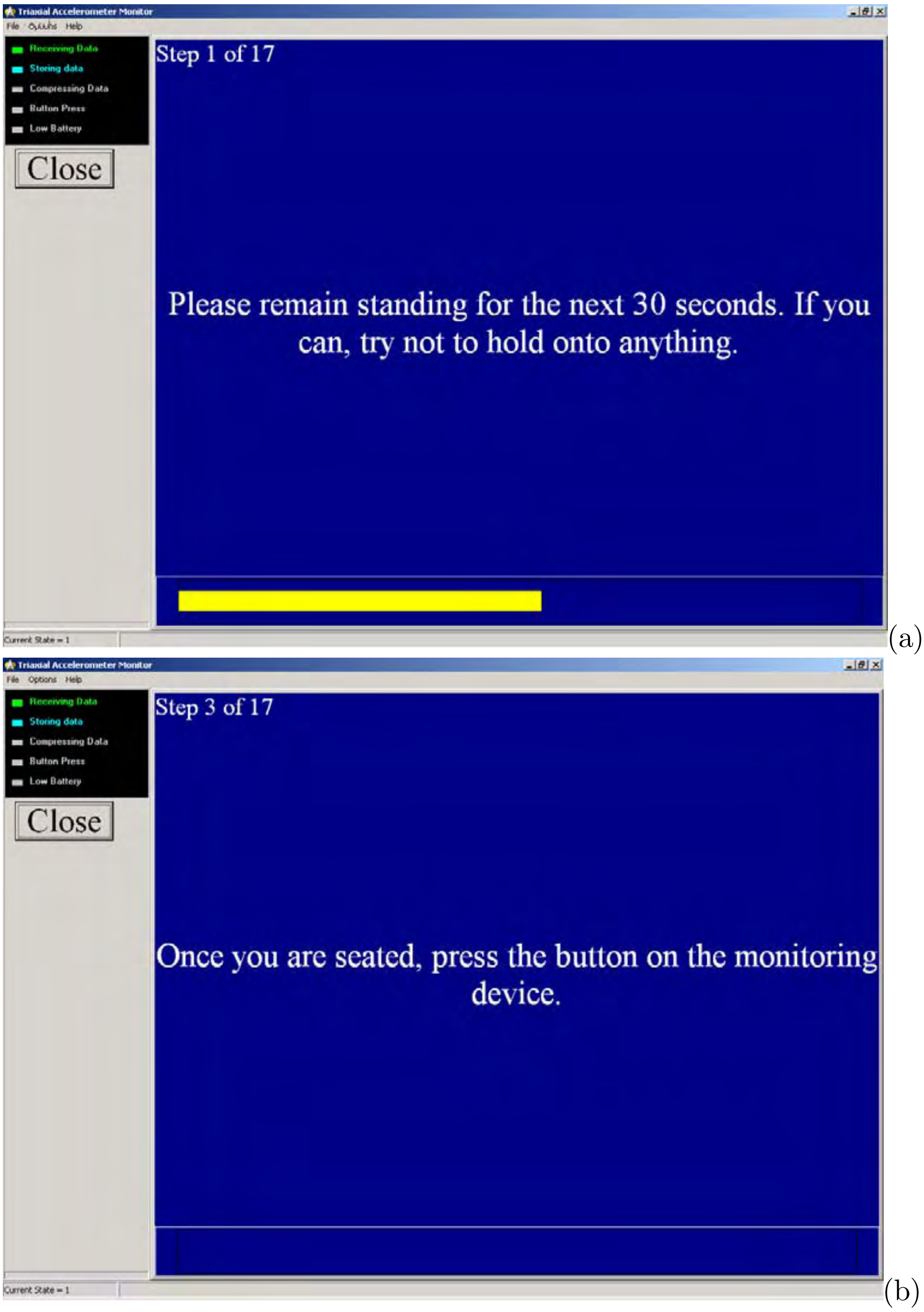


Figure 7.3: Two sample screens from the graphical user interface.

procedure was carried out was controlled by the subject rather than being dictated by the computer. As was indicated by the instructions, the subject was asked to carry out 11 movements, namely:

1. stand for 30 s (movement 1);
2. sit down (movement 2);
3. remain sitting for 10 s (movement 3);
4. stand up (movement 4);
5. remain standing for 10 s (movement 5);
6. walk (movement 6);
7. remain standing for 10 s (movement 7);
8. lie down (movement 8);
9. remain lying for 10 s (movement 9);
10. stand up (movement 10); and
11. remain standing for 10 s (movement 11).

The 10 s periods of standing were included to ensure that there was a clear period of rest between each movement. Each of the rest periods was held for at least 10 s before the next instruction was presented. A period of 5 s was allowed for each transition activity before the instruction to press the button was displayed. A period of 60 s was allowed for the walk. The entire test procedure took less than 5 minutes to complete.

Before commencing the unsupervised study each subject was guided through the test procedure by a supervising investigator to ensure that the subject was able to carry out the procedure and that the procedure was well understood. All subjects followed the same walking route through the office, and used the same office chair to sit on. As there was no bed or couch in the office, subjects lay down on the carpeted floor.

A log book was provided with the system. Subjects were asked to add an entry to the log each time that they used the system. The entry consisted of their code name, the date and time of the test, and any comments that they had about the system. At the conclusion of the study, subjects were interviewed to gauge their opinions of aspects of the system. Subjects were asked to comment on

- the useability of the TA unit;
- the useability of the rechargeable batteries;
- the useability of the graphical user interface; and
- the level of ease or inconvenience with which the routine was carried out.

A set of printed instructions that described in detail the experimental procedure was left with the computer system, together with a copy of the information and consent statements for the study. These were available to subjects at all times during the study.

The computer recorded the three-dimensional acceleration signal and the on/off state of the TA button. The data were sampled at 45 Hz and each recorded sample was time-stamped. The button presses acted as markers that indicated the completion of each activity. These provided an independent measure of activity identification and classification.

Data Analysis

Preliminary Processing Data were analysed retrospectively using purpose-built algorithms in Matlab version 6. The date and time of each test were extracted from the file and compared to the log book. If any discrepancies were detected, the investigator would speak to the subject to establish what actually occurred. If the discrepancy could not be resolved then the data were discarded. The number of tests undertaken by each subject was recorded.

The TA signal from each test was processed in the following way. Six button presses were expected. The number of distinct button presses in the data signal were counted. If there were too many button presses then the algorithm checked to see whether there was a double press, where the subject pressed the button twice in rapid succession. If so, then this was counted as a single button press. If there were still too many button presses then the signal was examined manually and any extraneous button presses were identified and removed.

It was not possible to have too few button presses and still complete the test routine. If there were too few button presses then the signal was discarded as the test routine was not completed.

Movement Identification Next, the activity detection algorithm was applied to the signal to distinguish between periods of activity and periods of rest. The six button presses provided markers in the signal that separated the different periods of activity. Ideally, there should have been exactly one period of activity that corresponded to the directed activity between each consecutive pair of button presses. However, between any two button presses there could be:

- no periods of activity;
- exactly one period of activity; or
- two or more periods of activity.

If there were no periods of activity then the directed activity was not detected. If there was exactly one period of activity then this should have been the directed activity. If there were two or more periods of activity then either (i) there was at least one period of extraneous activity; or (ii) there was a compound movement, in which two or more consecutive periods of activity each contained part of the directed movement. One example of a compound movement occurs when a subject stops moving during a period of walking. This introduces a period of rest into the middle of the movement, and the walking movement is subsequently characterised by two periods of walking activity, separated by a period of rest (standing). A second example of a compound movement occurs when a subject performs a lie-to-stand transition as a lie-to-sit transition, followed by a pause, followed by a sit-to-stand transition. In this case the one stand-to-lie transition is recorded as two component transitions, separated by a period of rest.

Every period of activity was inspected manually and classified as either (i) a directed movement; (ii) part of a compound movement; or (iii) an extraneous activity. Extraneous activities were categorised according to when they occurred. Possible categorisations included

- movement during standing;
- movement during sitting;
- movement during lying;
- movement during button press;
- movement before performing the directed activity (for example, walking to the chair before sitting down); and
- movement after performing the directed activity (for example, taking a step to regain balance after standing up).

Every period of activity was then classified automatically using the following procedure.

1. All of the periods of activity between two consecutive button presses were identified.

2. If there were no periods of activity then it was recorded that the directed activity was not detected.

3. If there was exactly one period of activity then this was classified as the directed activity.

4. If there was more than one activity then:

   (a) Any activities that occurred while the button was being pressed were classified as extraneous activities.

   (b) Any activities that occurred during a known period of rest (for example, during the 30 s period after the first button press during which the subject was standing) were also classified as extraneous activity.

   (c) The number of remaining activities between the two button presses were counted.

   (d) If exactly one activity was detected between the two button presses then this was classified as the directed activity.

   (e) If there was more than one period of activity remaining then the complete classification algorithm (refer to section 6.11) was applied to classify each of the periods of activity.

   (f) If the classification of exactly one of the periods of activity matched the directed activity then this was classified as the directed activity and the remaining periods of activity were classified as extraneous activity. Otherwise, the periods of activity were tested to see whether any of them could form a compound movement. When the directed movement was walking, successive periods of walking were classified as a compound walking movement. When the directed movement was a lie-to-stand transition, a lie-to-sit transition followed by a sit-to-stand transition was classified as a compound movement, and similarly for a stand-to-lie transition.

(g) If the directed movement was not uniquely identified by the classification algorithm and the periods of activity did not form a compound movement then a rule-based system was employed to determine the directed activity. The rule-based system chose the period of activity that was most likely to be the directed activity, based on the output of the classification algorithm and the time at which the period of activity occurred. Activities that occurred immediately after an instruction was given were deemed more likely to be the directed activities.

The period of activity that was automatically selected as containing the directed activity was compared to the period of activity that was identified manually and the classification accuracy of the automated system was evaluated.

After the periods of directed activity were identified, the periods of directed rest—sitting, standing and lying—were then identified. These were deemed to begin at the button press and to extend to the time at which the next instruction was presented to the subject (either 10 or 30 s later), and included any periods of extraneous activity that occurred during that time.

Statistical Analysis Once the movements were identified, all parameters deemed clinically relevant were extracted for each posture and activity. In each case the mean, median, standard deviation, minimum, maximum and range of each parameter were calculated for each subject and across all subjects. The parameters and statistics that were computed are summarised in table 7.1.

Three different methods were used to measure mean step rate. These were

1. the Fourier transform based algorithm (described in section 6.8.2);

2. the template matching algorithm (described in section 6.8.3), applied to the signals from all three axes with a majority vote at the end; and

3. the template matching algorithm applied only to the z-axis signal.

The median step rate and the standard deviation between steps were obtained using the third of these methods. All of the other parameters were obtained using the methods described in chapter 6.

The mean and standard deviation for each parameter were used to assess the consistency of the data. The mean values were compared to the mean values that were expected, based on the literature and on the supervised laboratory studies.

movement	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
tilt angle	$\surd$		$\surd$		$\surd$	$\surd$	$\surd$		$\surd$		$\surd$
postural sway	$\surd$										
duration	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
SMA	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
step rate - median						$\surd$					
step rate - mean						$\surd$					
step rate - std dev						$\surd$					
median acceleration x,y,z-axes, and ρ	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
mean acceleration x,y,z-axes,and ρ	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
std dev acceleration x,y,z-axes,and ρ	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
min acceleration x,y,z-axes,and ρ	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
max acceleration x,y,z-axes,and ρ	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
range acceleration x,y,z-axes,and ρ	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$

Table 7.1: Descriptive statistics that were measured for each of the periods of activity and rest. Movements are: 1. stand, 2. stand-to-sit, 3. sit, 4. sit-to-stand, 5. stand, 6. walk, 7. stand, 8. stand-to-lie, 9. lie, 10. lie-to-stand, and 11. stand.

The standard deviations measured the variability (and hence also the repeatability) of the measurements for each subject and between subjects.

The mean parameter values obtained across all subjects were compared across the different activities and resting postures. Boxplots and hypothesis tests were used to determine whether two sets of data had different mean values. If both data sets were normal (tested with the D'Agostino Omnibus normality test [57]) and had the same variance (tested with the Modified-Levene equal-variance test [101, 135]), then the 2-sample t-test was used. Otherwise the Aspin-Welch Unequal-Variance test or the Wilcoxon Rank-Sum test was used. The significance level was set at 0.05 in all of the tests (i.e. if the probability that the means of the two sets are the same is less than 0.05 then there is said to be a statistically significant difference in the means of the two data sets).

As an additional task, the walking detection algorithm was applied to all of the detected activities. This was done in order to evaluate the performance of the walking detection algorithm (described in section 6.8.4) on walking patterns that were not rigorously controlled. The performances of each of the three methods listed above were evaluated separately. The algorithm illustrated in figure 6.27 was then used to discriminate between periods of walking and periods of other activity. This algorithm was used with a two-stage cyclic test that involved use of both the Fourier transform based algorithm and the template matching algorithm, and is shown in the flowchart of figure 7.4. When the cyclic test was applied the period of activity was first tested using the Fourier transform based algorithm. If this classified the activity as cyclic then the cyclic test returned a true response. If the Fourier transform based algorithm did not classify the activity as cyclic then the period of activity was tested using the template matching algorithm applied to the z-axis alone. If this classified the activity as cyclic then the cyclic test returned a true response. Otherwise the test returned a false response.

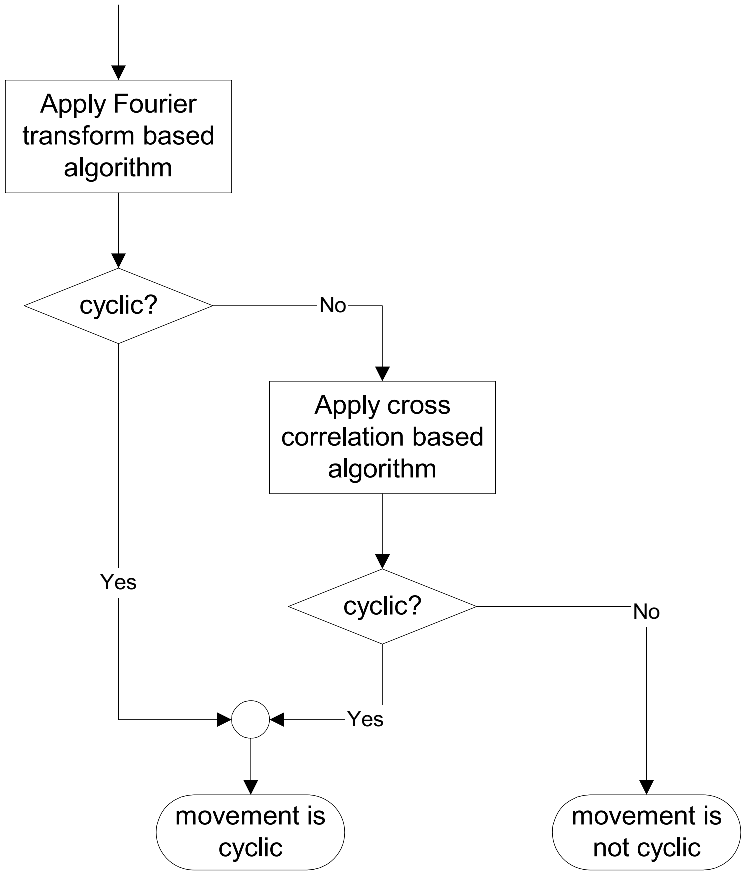
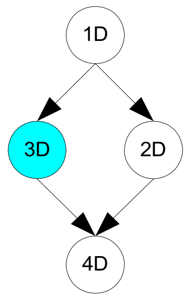


Figure 7.4: Flowchart showing the processing that was used within the cyclic activity testing block of the walking detection algorithm.

7.6 Experimental Procedure for the Supervised Home Study of Directed Movement (study 3D)



Introduction

The purposes of this study were to

- evaluate the performance of the system; and
- collect representative data from a normal subject during directed movement in a supervised home setting.

In this study the movements were directed and supervised but the study took place in a normal home rather than in a controlled laboratory environment. This provided a measure of the effect of the environment on the way in which the subject performed the routine. The daily repetition of the test by the subject allowed the data to be tracked longitudinally.

Setting

The study was carried out in the home shown in figure 4.3b.

Equipment

The same TA system was used in this study as was used in study 2D. However, in this study, the instructions to the subject were presented orally as well as visually.

Subjects

The investigator (a healthy 28 year old female) also acted as the subject for the study.

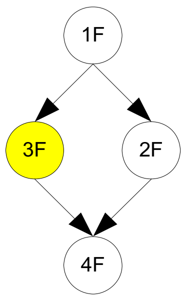
Experimental Procedure

The routine was identical to the routine carried out in study 2D. The computer was installed in a bedroom of the house. The subject stood, sat and lay in this room. The subject walked from the bedroom through the kitchen to the lounge room, through the dining room to the kitchen and back to the bedroom. The subject was asked to carry out the routine at least once a day over a 65-day period.

Data Analysis

The procedure for data analysis was identical to that used in study 2D.

7.7 Experimental Procedure for the Supervised Home Study of Free Movement (study 3F)



Introduction

The supervised home study of free movement was a feasibility study to evaluate the performance of the TA system when the subject was engaged in free-living activity at home. The aims of the study were

1. to collect data on the complex and arbitrary movements and sequences of movements performed in free-living;

2. to evaluate the performance of the classification algorithm (refer to section 6.11) on signals recorded during free-living; and

3. to introduce and assess the impact of a heuristic overlay to the classification algorithm for the classification of movements during free-living.

Setting

The study was set in the same home as the study 3D and occurred during the same 65-day period.

Equipment

The equipment consisted of the same TA system that was used in study 3D and a diary.

Subjects

The investigator also acted as the subject for this study.

Experimental Procedure

The subject wore the TA device and recorded all movements and timing in the diary on any days during the study period when she spent at least half the day at home. This allowed the collection and analysis of signal data that included complex and arbitrary movements of free-living.

Data Analysis

Preliminary Processing Data were analysed retrospectively using Borland Delphi version 5, Matlab version 6 and the statistical software package NCSS (Dawson Edition). The number of samples received during the monitoring period was compared to the expected number of samples transmitted (45 samples per second $\times$ duration of monitoring period) to determine the percentage of transmitted data that was received. This provided a measure of the reliability of the wireless communications in this setting.

Movement Identification The data from the TA during these periods was processed using the classification framework and algorithms described in chapter 6. A 1 s window was applied to the signal and each window was classified as containing either activity or rest using the activity detection algorithm (section 6.5). The complete classification algorithm (section 6.11) was then used to identify and classify the activities and postural orientations. The periods of rest were subclassified as upright or lying, and then as either sitting, standing, or a subposture of lying. Baseline data on tilt angles and SMA for use in the classification algorithm were obtained from the routine of directed movement that was carried out on the same day (refer to section 7.6).

The periods of activity were tested for falls. If a fall was detected then this was logged, together with parameters of peak acceleration, duration, SMA and postural orientation after the period of activity. In addition, all acceleration spikes in the magnitude vector exceeding 1.8 g for at least 3 consecutive samples were logged, together with their amplitude and duration as these potentially contained data pertaining to stumbles or other near falls. If a period of activity was not identified as a fall then it was classified as walking, a transition or some other activity using the algorithms described in chapter 6.

The automated signal classifications were compared to the movements described in the subject's diary. For each diary entry that described a specific movement, the classifier output for the same time ($\pm 30\,\mathrm{s}$) was checked. If the classifier output agreed with the diary entry then the movement classification was deemed correct. If the classifier output did not agree with the diary entry then the movement classification was incorrect. This provided a measure of the accuracy of the classification algorithm on these occasions.

Additionally, the acceleration patterns corresponding to other, more complex movement patterns that were described in the diary were identified and examined.

Heuristic Decision Making The activity classification algorithm identified each movement in isolation, without regard to whether or not the resulting pattern of movements was reasonable. For example, it was possible for the activity classification algorithm to classify a sequence of movements as:

$$\textit{sitting} \rightarrow \textit{sit-to-stand transition} \rightarrow \textit{sitting} \rightarrow \textit{walking},$$

although such a sequence can never be carried out. Clearly, the second period of sitting should actually be a period of standing. A rule-based system could be used to identify and correct this error.

A heuristic overlay was developed in order to check the sequence of classifications made by the classification algorithm. The system inspected the sequence of classified movements, movement by movement, in chronological order. If an inconsistency was identified then changes were made to the sequence of classifications so that the sequence became consistent. The rules that were applied are listed in figure 7.5.

This resulted in a new set of classifications. This new set was compared to the set of movement patterns described in the diary and the classification accuracy was evaluated.

sit → stand-to-sit

- If the rest state after the transition is *standing* then reclassify the *stand-to-sit* transition as a *sit-to stand* transition.
- Else, if the rest state after the transition is *sitting* then reclassify the *stand-to-sit* transition as *other movement*.
- Else (the next rest state is *upright*, but not subclassified) classify the next rest state and then return to classify the activity.

stand → sit-to-stand

- If the rest state after the transition is *sitting* then reclassify the *sit-to stand* transition as a *stand-to-sit* transition.
- Else if the rest state after the transition is *standing* then reclassify the *sit-to-stand* transition as *other movement*.
- Else (the next rest state is *upright*, but not subclassified) classify the next rest state and then return to classify the activity.

sit → walk

- If the duration of the *sitting* period is short and the activity before the *sitting* period is *other movement* then reclassify the *other movement* as a *sit-to-stand* transition and the *sitting* state as *standing*.
- Else assume that the *sit-to-stand* transition is contained in the same period of activity as the *walk* and was not detected separately.

upright resting state, not subclassified

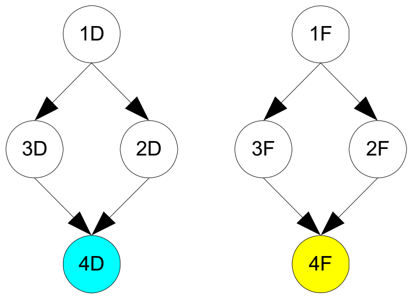
- If the activity after the *upright* resting state is *walking* then classify the *upright* resting state as *standing*.
- Else, if the activity before the *upright* resting state is a *sit-to-stand* transition then classify the *upright* resting state as *standing*.
- Else, if the activity before the *upright* resting state is a *stand-to-sit* transition then classify the *upright* resting state as *sitting*.
- Else, if the activity after the *upright* resting state is a *sit-to-stand* transition and this is consistent with the next resting state then classify the *upright* resting state as *sitting*.
- Else, if the activity after the *upright* resting state is a *stand-to-sit* transition and this is consistent with the next resting state then classify the *upright* resting state as *standing*.
- Else, if the activity before the *upright* resting state is a *lying-to-upright* transition then classify the *upright* resting state as *sitting*.
- Else classify the *upright* resting state as the same as the previous resting state, and reclassify the activity before the *upright* resting state as *other movement*.

upright-to-upright transition, not subclassified

- Classify the *upright-to-upright* transition based the resting states before and after the transition.
- If the resting state after the activity is *upright* but not subclassified then subclassify the resting state and then return to classify the activity.

Figure 7.5: Heuristic rules applied in study 3F to classify postures and activities of free movement.

7.8 Experimental Procedure for the Unsupervised Home Study of Directed and Free Movements (studies 4D and 4F)



Introduction

The unsupervised home study was designed as a pilot study for the TA system. The directed and free movement components were combined in this study. Each morning subjects carried out the directed routine. The results of the directed routine were used for longitudinal tracking of movement-specific parameters and to provide baseline data with which to identify the placement of the TA unit. The free movement component was used to evaluate the technical performance and useability of the system, and to longitudinally track general parameters of movement, including amount of time spent in activity and energy expenditure.

The study had four specific aims:

1. to assess the technical performance of the system in more homes;
2. to assess the useability of the system for an elderly cohort;
3. to determine normal parameter values and ranges for a healthy elderly cohort; and
4. to test and validate the data processing algorithms in an unsupervised setting with an elderly cohort.

Setting

The study was carried out in the homes of the subjects.

Equipment

Each subject was given a TA system (computer, receiver and TA unit), four rechargeable AA batteries and a recharger, daily and weekly health questionnaires, and a falls diary. All systems were tested in the laboratory for at least 2 days before being installed in the field.

Subjects

Subjects were recruited through the Prince of Wales Medical Research Institute (POWMRI). Subjects were required to be aged over 65 years, living independently at home, and able to use the TA system. Subjects were selected from a list of subjects who had previously participated in a study on the effect of exercise on the risk of falls, conducted by the POWMRI. The investigator was blind to the selection of subjects. A researcher from the POWMRI contacted potential subjects and explained the study to them. If they were interested, an information and consent statement was posted to them. A copy of the information and consent statement is included in appendix B. This was followed up a week later with a phone call from the researcher to establish whether the person was still interested in participating. If so, their name and contact details were passed on to the investigator (the current author) who then contacted the person to arrange a time to visit. During the home visit the investigator showed the person the equipment and explained the trial protocol again. If the person was still willing, they were asked to give written consent, and the TA system was set up in the home.

Experimental Procedure

The study extended for a period of up to 13 weeks. The computer and TA receiver were set up in a location in the subject's home that provided optimal coverage of the TA unit around the home and that was convenient for the subject.

The subject's health and medical histories were assessed at the beginning and the end of the study using the Stanford University School of Medicine Health Assessment Questionnaire (HAQ) Disability Index and Pain Scale[1] [36, 78, 79, 189] and a customised medical history questionnaire. The coop/wonca health questionnaire [177] was also completed by the subject at these times. The HAQ Disability Index measures the ability of the subject to function in daily life through a series of questions on a range of ADLs and IADLs. It is scored from 0 to 3, where 0 indicates no

[1] The Stanford HAQ is available from the Department of Immunology and Rheumatology at Stanford University in Stanford, California, USA.

disability and 3 indicates severe functional disability. For the Pain Scale, subjects were asked to indicate the level of pain that they had suffered in the last week. The pain scale is scored from 0 to 3, where 0 indicates no pain, and 3 indicates severe pain. The medical history questionnaire obtains information on significant medical illnesses and conditions and current medications. The coop/wonca health questionnaire measures overall health status with six questions encompassing physical, emotional, social and overall health. Each question is given a score from 1–5, with 1 indicating the best response and 5 indicating the worst response. The scores from the six questions are summed to give a total score for the questionnaire. Copies of the questionnaires are included in appendix C.

The subject was trained in the use of the TA unit and in the required tasks. Figure 7.6 shows the tasks that were required of the subject each day. The subject was required to place a rechargeable battery into the TA unit, attach the unit at the waist, and wear it for the rest of the day. In addition, once each day the subject was required to carry out the same routine that was used in study 2D (section 7.5). Instructions were presented orally and visually during the routine. The subject was also required to complete a daily question on overall health status and a weekly health questionnaire.

The daily question was:

> "How would you rate your health today compared to yesterday?".

The subjects were required to choose between five options:

- much better;
- a little better;
- about the same;
- a little worse; and
- much worse.

The question was scored on an ordinal scale from 1 to 5, with "much better" registering the lowest score.

The weekly health questionnaire was the coop/wonca questionnaire [223]. This questionnaire was administered by the investigator, either face-to-face or by telephone.

In the morning

1. Remove a battery from the recharger unit
2. Insert the battery into the monitoring device
3. Attach the monitoring device to your waist
4. Go to the computer.
5. Push the mouse to "wake up" the computer screen.
6. Once you are standing and ready to start the daily routine, press the button on the monitoring device to start.
7. Continue to follow the instructions given by the computer until the daily routine is complete.
8. Wear the monitoring device for the rest of the day.

If you are going out

You don't need to do anything - you can continue to wear the monitoring device while you are out.

However, if you are concerned about losing the monitoring device while you are out, or do not want to wear it while you are out, then you can take it off and place it near the computer until you come home. When you come home again, simply pick up the monitoring device and attach it to your waist. You do not need to do anything else - there is no need to press the button.

In the evening

1. Complete the daily health questionnaire for today.
2. Remove the monitoring device from your waist.
3. Remove the batter from the monitoring device.
4. Place the battery in the recharger unit.
5. Plug in the recharger unit, turn on the power, and allow to recharge overnight.

Figure 7.6: "How to use the ambulatory monitor"—the tasks required by subjects in order to use the TA system.

Each subject was asked to attach the TA unit at the waist after getting up in the morning, and to wear the unit until going to bed in the evening. Subjects were told that they could remove the TA unit if they were going out, although this was not necessary and the unit could be worn outside the home. If subjects were going out and planned to remove the TA unit, they were asked to place it beside the receiver unit until they returned home, whereupon they were requested to reattach the unit at the waist.

When the system was installed in the subject's home the most convenient time for carrying out the daily routine was discussed with the subject. It was explained that the routine could be carried out at any convenient time during the day, and that the computer could be used to issue a reminder to carry out the routine. All subjects elected to carry out the routine in the morning, after getting out of bed and dressing. The automated reminder was set to activate if the daily routine had not been commenced by the time nominated by the subject.

When the automated reminder was activated the computer commenced execution of the daily routine programme. The subject was asked to press the button on the monitoring device when standing and ready to commence the daily routine. This instruction was presented on the monitor and was also presented orally once a minute until the button was pressed by the subject or ten minutes had elapsed. If the subject did not commence the routine within ten minutes of the reminder activation then the oral reminders stopped but the instruction remained on the GUI until the routine was undertaken.

The plan for the daily routine, including choice of chair, bed and walking route were determined when the system was installed in the subject's home. Each subject was guided through the routine by the investigator several times until she or he felt confident and could complete the daily routine without assistance from the investigator. Subjects also practised using the rechargeable batteries and attaching the TA unit to the waist in the presence of the investigator until they felt confident.

Once the subject was comfortable with the system she or he was left alone with the system for one week. The following week, the subject received a follow-up visit from the investigator. The training that was provided on the first visit was repeated on this visit, and any questions raised by the subject about the system were answered. The investigator asked the subject for feedback on use of the system. The data captured by the system were recorded onto compact disc by the investigator using a portable compact disc writer. Once this was successfully completed, the data were removed from the computer's hard disk to allow space for future data collection.

During the training, the TA unit was attached above the right anterior superior iliac spine of the subject. However, subjects were not told that they needed to wear the unit in this position, merely that it had to be attached at the waist.

Once every week the investigator contacted each subject to complete the coop/ wonca health questionnaire, either by telephone or by visiting. The investigator visited each subject at least once every two weeks to collect the data from the system, and to ensure that the system was running properly.

Subjects were also given a falls diary. In the event of a fall or stumble, subjects were asked to press the button on the TA unit if it was being worn, and to make an entry in the falls diary noting the time, location, nature and cause of the event. Subjects were also invited to make notes about their daily activities in the falls diary although this was not required of them.

Mid-way through the study, a short-form physiological assessment was conducted on each subject to assess falls risk. The assessment was developed by Lord *et al.* and has been well validated [141, 142, 143, 144, 146]. This assessment was carried out in the subject's home. Edge contrast sensitivity, hand reaction time, proprioception, knee extension (quads strength) and balance were assessed and a measure of falls risk was determined. The falls risk was graded as one of (i) very low; (ii) low; (iii) mild; (iv) moderate; and (v) marked.

At the conclusion of the study, the health and medical questionnaires that were applied at the start of the study were reapplied to each subject. Subjects were then interviewed to formally obtain feedback on their use of the TA system.

Data Analysis

Data were analysed retrospectively. The procedure for analysing the data from the daily routine was identical to that used in study 2D. The data from the free movements carried out during the rest of the day were processed in a similar manner to those from the supervised home study of free movement (section 7.7), except that the movements were not classified beyond discrimination between activity and rest. The procedure that was used for this study is described below.

The time stamp on each data sample was examined to determine whether or not any data had been lost. The amount of missing data was recorded on an hourly and daily basis for each subject. This provided a measure of the reliability of the wireless communications in these settings.

The TA data signals were median filtered using a filter of length 13 samples. (This value was found to be one of the optimal lengths in the activity detection algorithm of section 6.5.) The signals were then high-pass filtered ($f_c = 0.25\,\mathrm{Hz}$) to extract the body acceleration component. The FIR filter described in section 5.2.7 was used to achieve this. The data were then processed in one second blocks.

The incoming signal was tested to determine whether or not the device was being worn. The a.c. magnitude vector, ρ_{ac}, was computed and averaged over the last 60 s. The mean value was compared to a threshold to determine whether or not the device was being worn. The threshold value was determined from the results of the study of section 6.4. It was set as 0.0325 $g/$ s, a value that corresponded to the mean plus one standard deviation of ρ_{ac} when the device was not being worn, but which was less than the mean value of ρ_{ac} when the device was being worn and the subject was resting. If the 60 s average of ρ_{ac} was less than the threshold then the subject was deemed to not be wearing the device over that period.

If the subject was wearing the TA device then the SMA was computed for each second of data. The activity threshold was set as $th = 135 \times 10^{-3}$ g, as per the results of section 6.5. If the 1 s-averaged SMA exceeded the threshold then the subject was classified as being engaged in activity during that period.

All periods of activity were tested for fall events, and all abnormally large acceleration spikes (those exceeding 1.8 g on the magnitude vector for at least 3 consecutive samples—refer to section 6.7.2) were logged.

An overview of this processing is shown in figure 7.7.

The parameters extracted from the collected data were collated hourly and daily for each subject and tracked longitudinally. The parameters sets were tested for correlations with self-reported health status. These parameters were:

- the time at which the system started collecting data that day;
- the time at which the system stopped collecting data that day;
- the percentage of transmitted data that was captured by the receiver unit;
- the percentage of time for which the TA unit was worn;
- the percentage of time for which the subject was engaged in activity;
- the total and mean SMA during periods of activity; and
- the total and mean SMA during periods of rest.

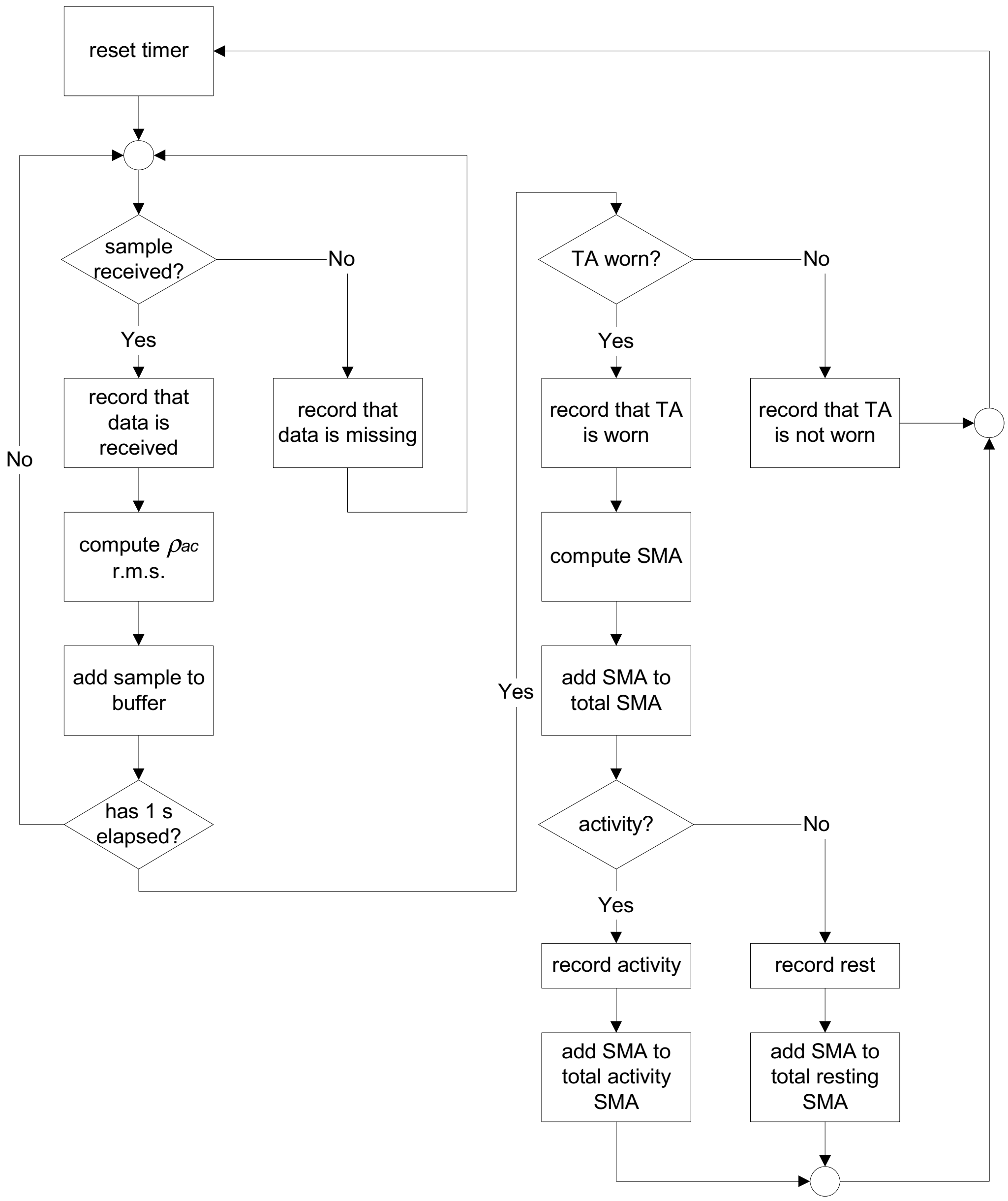


Figure 7.7: Flowchart of the sample-by-sample processing of the TA data. Every second the signal was tested to determine whether the subject was wearing the device and, if so, whether the subject was engaged in activity or rest. Parameters were recorded on an hourly and a daily basis.

7.9 Comparisons Between Directed Routine Data Sets

The performance of subjects in carrying out the directed routine was evaluated in a supervised laboratory setting (these studies were described in chapter 6), in an unsupervised laboratory setting (study 2D), in a supervised home setting (study 3D), and in an unsupervised home setting (study 4D). All of these studies used cohorts of normal, healthy subjects. In study 4D a group of elderly subjects was used.

The purpose of repeating the testing in different settings was to determine the effect of the setting and the presence of supervision on the way in which the subjects carried out the routine. The parameter values obtained in each study were compared, using the same testing procedures that were described in section 7.5. The variabilities in the parameters were compared. Classification accuracies were compared. The number of extraneous movements were tallied and compared. The number of compound movements were compared. The data sets from the directed routine were then compared between the cohorts of young subjects and the cohort of elderly subjects, using the same procedures.

7.10 Chapter Conclusion

A methodology for unsupervised home monitoring of free-living subjects was designed. This methodology consisted of two components: a routine of directed movement from which clinically sensitive parameters were extracted and tracked longitudinally, and a period of free movement in which the TA monitored the subject for abnormal events such as falls. Each component of the system was tested systematically in a series of experimental studies that included supervised and unsupervised laboratory monitoring of directed movements; supervised and unsupervised home monitoring of directed movements; and supervised and unsupervised home monitoring of free movements. The results of these studies are presented in the next chapter.

Chapter 8

Experimental Results and Discussion

8.1 Overview

Chapter 7 presented the design of a series of experiments to assess the performance of the TA in monitoring of human movement patterns. Data were collected from movements performed during a directed routine and during free movement. The directed routine was used to track parameters of specific movements over time. It was also used to identify the placement of the TA on the subject. The monitoring of free movement was used to identify abnormal events and to track general parameters of movement, including hourly and daily SMA and the amount of time spent in activity.

The performance of the TA in monitoring the directed routine was studied in supervised and unsupervised laboratory and home environments. The performance of the TA in monitoring free movement was studied in supervised and unsupervised home environments. Figure 8.1 summarises the studies that were undertaken. The laboratory studies of the daily routine were undertaken using cohorts of normal subjects. The supervised home studies of directed and free movements were undertaken using the same normal subject in the same home environment. The unsupervised home studies of directed and free movements were undertaken together in a pilot study of the TA in a community setting, using a cohort of healthy elderly subjects.

The studies of directed movement in a supervised laboratory setting (study 1D) were used to develop the algorithms used in the classifier and are presented in chapter 6. This chapter presents the results of the other studies. Firstly, the user feedback from all of the subjects is presented. Next, the results for the studies

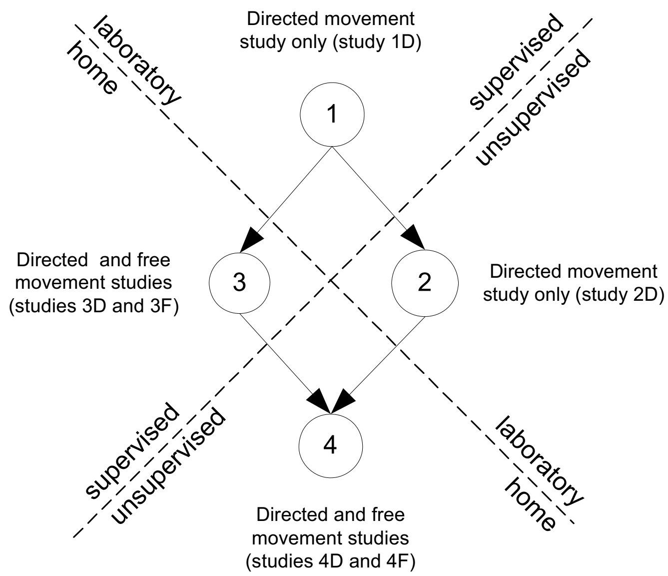


Figure 8.1: Experimental studies undertaken in the current work. The codes 'D' and 'F' are used to represent the studies of directed and free movement, respectively. The studies were 1D: supervised laboratory study of directed movement, 2D: unsupervised laboratory study of directed movement, 3D: supervised home study of directed movement, 4D: unsupervised home study of directed movement, 3F: supervised home study of free movement, and 4F: unsupervised home study of free movement.

of directed movement (studies 2D, 3D and 4D) are presented and compared. The results of the feasibility study for monitoring of free movement (study 3F) are then presented. Finally, the results of the free movement component of the pilot study (study 4F) are presented.

8.2 User Feedback

Studies 2D, 3D and 3F

The subjects who participated in studies 2D, 3D and 3F all reported that they found the TA unit comfortable to wear and that the system was easy to use in every respect. However, the subject who participated in studies 3D and 3F found changing the battery each day inconvenient.

All subjects reported that the instructions on the graphical user interface were clear and easy to follow. All subjects stated that the directed routine was easy to carry out, caused no inconvenience, and required a minimal time commitment.

A subject who participated in study 2D suggested that instructions be presented audibly as well as visually on the graphical user interface so that there was no need to continually watch the user interface while carrying out the routine. When this suggestion was made to the other participants in the study, they were in agreement. Audible instructions were consequently incorporated into the test procedures for the later studies of directed movement (studies 3D and 4D).

Studies 4D and 4F

The elderly subjects who participated in the pilot study used the TA system far more extensively than the other subjects, and hence had more detailed comments on the system. They also raised issues that were not raised by the younger subjects, which pertained to their lack of familiarity with the technology and their more fragile health status.

All of the subjects who participated in the pilot study were initially nervous about using the technology, for fear of damaging the equipment, particularly the computer. It was emphasized to the subjects that they could not cause any damage to the system.

TA Unit Subject feedback with regard to the wearability of the TA unit varied. All subjects agreed that the unit was comfortable and that they forgot that they were wearing it. However, the attachment clip was too loose for two of the female subjects who found that the unit tended to slip off when bending over or toileting.

One female subject found it limiting that she was unable to wear dresses due to the need for attachment at the waist. However, another female subject chose to wear the unit attached to undergarments beneath dresses and she reported that she found this arrangement completely comfortable.

Three of the subjects found that placement of the unit was very important for comfort and the prevention of bruising. The first of these subjects found that the unit was most comfortable when worn in the middle of the waist as it dug into her hip when attached above the iliac spine and caused bruising. The second of these subjects found that the device was most comfortable when worn on the right side. When he wore the unit above the right anterior superior iliac spine it knocked against his right arm and he was concerned about this causing bruising. The third of these three subjects found that she needed to change the location at which the TA was worn every three or four days due to pressure on the body from the unit. She alternated between wearing the unit above the right and left anterior superior iliac spines. The other three subjects reported no problems with discomfort or bruising and wore the unit above one of the anterior superior iliac spines for the duration of the study.

TA Batteries All subjects initially found changing the battery difficult but in the final assessment all agreed that changing the battery posed no problems. Subjects agreed that introducing a recharger cradle that would remove the need to change the battery would be simpler to use, but did not feel that this was an important issue.

TA Push Button Two subjects found that the push button on the TA unit was too small and sharp, and had concerns that it would pierce the skin. A layer of padding was attached to the button for these two subjects. This both enlarged and softened the surface of the button and solved this problem. A third subject found that the button was difficult to reach as the top of the TA unit became buried under soft tissue when attached at the waist.

Computer None of the subjects interacted with the computer other than to follow the instructions given in the daily routine. One subject said that he would like to learn how to use computers, but felt that he was too old. None of the other subjects expressed any interest in using the computer. All of the subjects said that they would have preferred the system without the computer.

Several subjects observed that the receiver and computer system formed a very bulky arrangement that would be particularly inconvenient for people living in small units, and that the entire system appeared very expensive. These subjects felt that the computer monitor should not be included with the system as the audible instructions were sufficient and the graphical user interface was not necessary. They would also have preferred to see the receiver and computer reduced in size.

Daily Routine All subjects found that the daily routine was easy to manage, and did not pose any inconvenience. All subjects agreed that the instructions were very clear and easy to follow.

System Overall All subjects stated that the system was easy to use “once you got used to it” and that using it did not cause any inconvenience.

All of the subjects felt that the concept of a “smart” personal alarm system that could automatically detect falls would be very valuable. One subject said that he could not see any value in identifying early indicators of falls or changes in health status. He felt that education, exercise regimes and environmental monitoring to detect hazards were far more important. He also felt that the system needed to work outside as well as in the home. The other five subjects supported the concept of home monitoring for early identification of changes in functional status. Monitoring at home to reduce the need to travel to the clinic was also seen as a positive feature. One subject remarked that “if this system could avoid a trip to the specialist, it’s worth its weight in gold”.

8.3 Studies of Directed Movement

8.3.1 Introduction

Four studies of directed movement were undertaken. These studies were set in:

1. a supervised laboratory environment (study 1D);
2. an unsupervised laboratory environment (study 2D);
3. a supervised home environment (study 3D); and
4. an unsupervised home environment (study 4D).

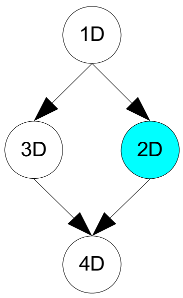
The 1D studies were used to develop and evaluate the classification algorithm and parameter extraction techniques that are described in chapter 6. Studies 2D and 3D were undertaken to determine the effect of supervision and environment on the way in which subjects performed the routine. In study 4D a cohort of healthy elderly subjects carried out the directed routine in an unsupervised home environment on a daily basis. The way in which these elderly subjects performed the routine was tracked longitudinally and compared to the way in which the younger subjects performed the routine.

In the following sections the subject cohorts for each study are described and the number of times that each subject used the system is given. The preliminary processing and movement identification are then presented for each study. The statistical analyses are presented for all studies and the results are compared across studies.

Subject	Gender	Age	Repetitions
1	F	23	6
2	F	25	4
3	M	41	5
4	M	35	3
5	F	25	3
6	M	25	14
7	F	28	2
8	M	32	15
9	F	56	6
10	M	44	6
11	M	49	1

Table 8.1: Characteristics of subjects participating in study 2D.

8.3.2 Unsupervised Laboratory Study of Directed Movement (study 2D)



The unsupervised laboratory study was described in section 7.5. Normal, healthy volunteers from the Centre for Health Informatics (CHI) carried out a short routine consisting of basic daily activities while wearing a TA unit. The testing was conducted, unsupervised, in the offices of CHI.

Use

Eleven subjects participated in the study. Subject characteristics are listed in table 8.1. Several of the female subjects who participated in study 2D stated that they had not carried out the routine on days when they were wearing skirts or dresses as they did not wish to lie down on the carpet of the office when so attired. Other subjects stated that they had not always carried out the routine because they had been too busy, out of the office, or because they had forgotten.

Data Analysis

Preliminary Processing The record of tests that was compiled by the subjects in the log book agreed with the test files on the computer in all respects (number of tests carried out, date and time at which tests were performed, and the subject who performed the test). Sixty-five iterations of the routine were performed and they were all included in the analysis.

All subjects successfully completed the test routine on each occasion, with the exception of subject 7, who did not carry out the lying down component in one of the two test routines performed. All activities and rest periods after the walk were disregarded for this iteration of the routine. All other movements were included in the analysis. This resulted in 710 directed movements being included in the analysis. Of these, 323 were periods of activity and 387 were periods of rest.

The number of button presses recorded in each iteration of the routine were counted. Six button presses were expected each time. There were more than the six expected button presses in nineteen of the routine iterations. On eighteen of these occasions, the subject had pressed the button twice in rapid succession, as part of the same button press action. In these cases, the anomaly was automatically corrected and the first of the two button presses was used as the marker to indicate completion of the last activity. On the remaining occasion, the subject had pressed the button twice at the start of the test. The first of the two button presses was removed manually and the test routine was considered to have commenced with the second button press.

Movement Identification When the activity detection algorithm (refer to section 6.5) was applied to the signals it correctly identified all 323 periods of directed activity and an additional 46 periods of extraneous activity. The extraneous activities occurred at various times during the routine. The greatest number (19) occurred while the subject was standing. They also occurred during button presses and due to movement before undertaking the next activity (for example, when a subject walked several steps to reach the chair before sitting down). Seven of the extraneous activities that were identified were false positives. These were caused by ringing artefact introduced into the signal by the filtering process (refer to section 5.2.7). These were identified by comparing the change in signal magnitude area of the high-pass filtered signal to the change in signal magnitude area of the signal before filtering. Table 8.2 lists the extraneous activities that were identified according to type.

One period of compound movement was identified. This occurred during a stand-

Type of movement	Occurrences
movement during button press	7
movement while standing	19
movement while sitting	3
movement while lying	1
walk to chair	4
walk to bed	1
pre-walk movement	4
false positives	7
Total	46

Table 8.2: Extraneous movements occurring during 65 iterations of the directed routine in study 2D.

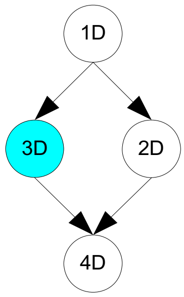
Iterations of routine ($N = 11$)	65
Directed activities	323
Directed rest periods	387
Total activities detected	369
Extra periods of activity detected	46
Compound movements	3
Directed activities correctly classified	316 (97.8%)
Directed activities incorrectly classified	7 (2.2%)

Table 8.3: Characteristics of collected data and classification results from study 2D.

to-lie transition where the movement was composed of a stand-to-sit transition followed by a sit-to-lie transition. This transition was correctly identified as a compound movement by the automated algorithm.

The automated algorithm correctly identified all but seven of the directed activities, leading to an overall activity classification rate of 97.8%. On seven occasions the algorithm incorrectly identified a period of extraneous activity as the directed activity. The results are summarised in table 8.3.

8.3.3 Supervised Home Study of Directed Movement (study 3D)



The supervised home study was described in section 7.6. One normal, healthy 28-year-old female carried out the same short routine that was used in the unsupervised laboratory study of directed movement. The testing was conducted in the subject's home.

Use

The subject carried out 62 repetitions of the routine over the 65 day testing period.

Data Analysis

Preliminary Processing Sixty-two iterations of the routine were performed and they were all included in the analysis. The subject successfully completed the test routine on each occasion but one in which she did not carry out the walking task. The walk period and the periods of standing preceding and following this were excluded from the analysis. All other data were included in the analysis. This resulted in 679 directed movements being included in the analysis. Of these, 309 were periods of activity and 370 were periods of rest.

The number of button presses recorded in each iteration of the routine were counted. Six button presses were expected each time. There were more than the six expected button presses in five of the routine iterations. On each of these occasions, the subject had pressed the button twice in rapid succession, as part of the same button press action. In each case the anomaly was automatically corrected and the first of the two button presses was used as the marker to indicate completion of the last activity.

Type of movement	**Occurrences**
movement during button press	3
movement while sitting	2
pre-walk movement	1
false positives	6
Total	12

Table 8.4: Extraneous movements occurring during 65 iterations of the directed routine in study 3D.

Iterations of routine ($N = 1$)	62
Directed activities	309
Directed rest periods	370
Total activities detected	321
Extra periods of activity detected	12
Compound movements	0
Directed activities correctly classified	308 (99.7%)
Directed activities incorrectly classified	1 (0.3%)

Table 8.5: Characteristics of collected data and classification results from study 3D.

Movement Identification When the activity detection algorithm (refer to section 6.5) was applied to the signals it correctly identified all 309 periods of directed activity and an additional 12 periods of extraneous activity.

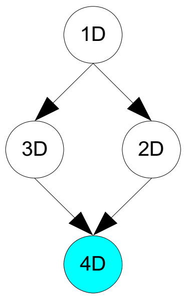
The extraneous activities occurred during button presses, while sitting, at the start of the period of walking, and due to false positives caused by ringing artefact introduced into the signal by the filtering process (refer to section 5.2.7). Table 8.4 lists the extraneous activities that were identified according to type. No periods of compound movement were identified.

The automated algorithm correctly identified all but one of the directed activities. On one occasion the algorithm incorrectly identified a period of extraneous activity as the period of directed activity. This led to an overall activity classification rate of 99.7%. These results are summarised in table 8.5.

Subject	Gender	Age
1	F	82
2	M	85
3	M	82
4	F	80
5	F	83
6	F	85

Table 8.6: Characteristics of subjects participating in the unsupervised home study.

8.3.4 Unsupervised Home Study of Directed Movement (study 4D)



The design of the unsupervised home study was described in section 7.8. The study was conducted in the homes of functionally independent, elderly, community dwelling subjects. Each morning the subjects were required to attach the TA unit to the waist and carry out a directed routine consisting of sitting, standing, walking and lying. Following this, subjects were required to wear the TA unit for the rest of the day as they performed their daily activities. They were also required to complete a daily health question, a weekly health questionnaire and a falls diary. The results pertaining to the directed routine are presented here. The results pertaining to the monitoring of free movement are presented in section 8.5.

Subjects

Six subjects participated in the study. Subject characteristics are shown in table 8.6. Other subject characteristics pertinent to the study of free movement are presented in section 8.5. All subjects were over 80 years of age, healthy and living independently at home.

Subject	no. days routine carried out	no. days routine missed	no. routine repetitions
1	92	0	96
2	78	0	80
3	66	17	69
4	59	10	59
5	60	8	61
6	48	18	52

Table 8.7: Details of daily routine performance in study 4D

Use

During the study period, 417 repetitions of the daily routine were recorded (table 8.7). Subjects 1 and 2 carried out the daily routine every day during the study. The other subjects did not carry out the daily routine on a number of occasions due to:

- confusion on how to use the system;
- technical difficulties with the system;
- being away from home; and
- going out for the day and not getting around to carrying out the routine.

Self-Reported Health Status

Most of the time subjects reported their daily health as being about the same as the previous day. This indicates that the subjects' health remained stable throughout the study period. The histogram in figure 8.2 shows the complete set of responses given by the six subjects.

Figure 8.3 shows the overall scores for the weekly coop/wonca test for each of the six subjects by date.

Directed Movement - Data Analysis

Preliminary Processing A total of 417 iterations of the daily routine were carried out. The routine consisted of a 30 s stand (movement 1), a stand-to-sit transition (movement 2), a period of sitting (movement 3), a sit-to-stand transition (movement 4), a period of standing (movement 5), walking (movement 6), a period of standing (movement 7), a stand-to-lie transition (movement 8), a period of lying (movement 9), a lie-to-stand transition (movement 10), and a period of standing

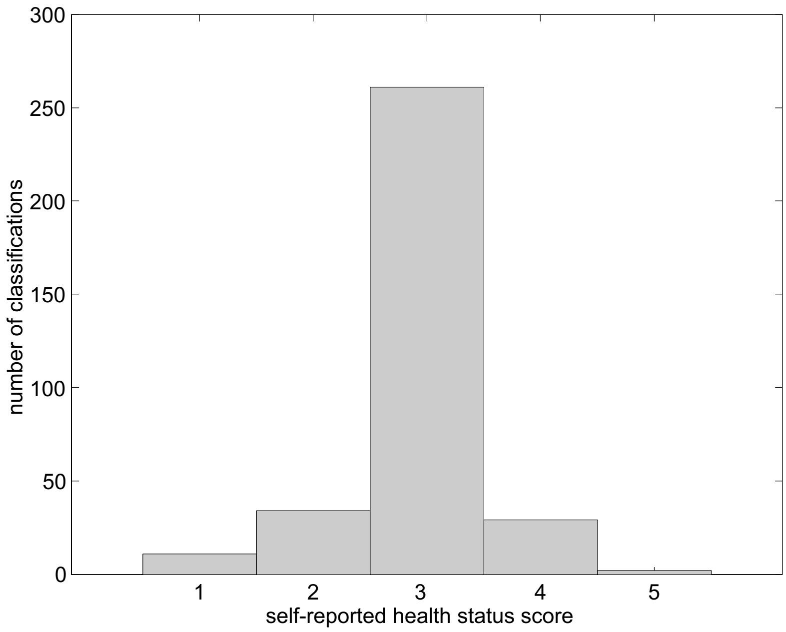


Figure 8.2: Histogram of self-reported daily health status ($N = 337$). The question asked was "How would you rate your health today compared to yesterday?", and the responses were 1. much better; 2. a little better; 3. about the same; 4. a little worse; and 5. much worse.

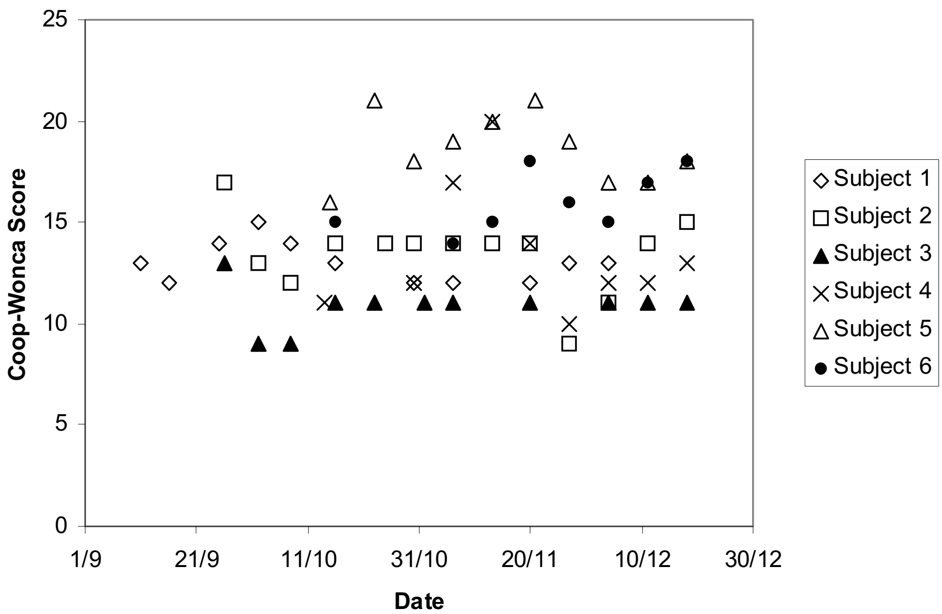


Figure 8.3: Self-reported weekly health status—scores from the coop/wonca health questionnaire for each subject. Lower scores indicate a better health status.

(movement 11). Of these, the following were discarded from the analysis due to either corruption of the signal[1], or failure of the subject to perform the movement in such a way that allowed unambiguous identification (for example, pressing the button at the wrong time, or not carrying out a movement):

- 7 instances of movement 1;
- 2 instances of movement 2;
- 4 instances of movement 3;
- 3 instances of movement 4;
- 4 instances of movement 5;
- 2 instances of movement 6;
- 14 instances of movement 7;
- 13 instances of movement 8;
- 13 instances of movement 9;
- 11 instances of movement 10; and
- 11 instances of movement 11.

All remaining instances were included in the subsequent analysis. This resulted in the analysis of 2054 directed activities and 2451 directed rest periods.

The number of button presses recorded in each iteration of the routine were counted. Six button presses were expected each time. There were more than the six expected button presses in 34 of the routine iterations. On 30 of these occasions, the subject had pressed the button twice in rapid succession, as part of the same button press action. In these cases, the anomaly was automatically corrected and the first of the two button presses was used as the marker to indicate completion of the last activity. On four occasions the subject had pressed the button at the wrong time (for example, in the middle of a period of lying) and these button presses were removed manually from the signal so that the signal data could be included in the statistical analysis.

[1] This occurred intermittently in the data from subject 2 due to a bad solder joint. There were also a small number of occasions when data were lost in transmission during a movement and these movements were excluded from the analysis.

Type of movement	Occurrences
movement during button press	264
movement while standing	64
movement while sitting	39
movement while lying	28
walk to chair	8
walk to bed	83
pre-walk movement	27
pre-routine movement	7
post-routine movement	0
other	35
Total	555

Table 8.8: Extraneous movements occurring during 417 iterations of the directed routine in study 4D.

Movement Identification When the activity detection algorithm (refer to section 6.5) was applied to the signals it correctly identified all of the 2054 periods of directed activity and an additional 555 periods of extraneous activity.

The extraneous activities occurred at various times during the routine. The most common cause of extraneous activity was the subject moving the TA unit in order to reach the button. Extraneous activities also occurred in the middle of periods of rest as subjects adjusted their postures, and when they took several paces before carrying out the next activity. For example, when instructed to lie down, some subjects would typically be standing several paces away from the bed and would need to move closer before they could lie down. When instructed to walk, some subjects would often take one or two steps and then pause before embarking on the period of walking. Table 8.8 lists the extraneous activities according to type.

103 periods of compound movement were identified by manual inspection. Most of these occurred during walking. They occurred because the subjects sometimes stopped for several seconds during the 60 s period of walking before continuing, and these interruptions were identified as periods of rest by the activity detection algorithm. Others occurred during the stand-to-lie transitions and the lie-to-stand transitions when the subject performed the movement in two stages; as a transition between standing and sitting, and a transition between sitting and lying. The compound movements are summarised in table 8.9. Almost all of the compound movements between standing and lying were performed by a subject 1. When the way in which she performed the routine was discussed with the subject, it eventuated that whenever she was wearing shoes that had been outside or that she had been working in, she performed the sit-to-lie transition by sitting down on the

Movement	Occurrences	Correctly Identified
walk	67	52
stand-to-lie	13	10
lie-to-stand	23	6

Table 8.9: Compound movements occurring during 417 iterations of the directed routine in study 4D.

bed, removing her shoes, and then lying down. To stand up again, she performed the procedure in reverse. If the shoes were loose slip-on shoes she was often able to kick them off rapidly without needing to reach down and remove them. On these occasions the stand-to-lie transition was recorded as a single movement. On the other occasions the movement was recorded as a compound movement. Hence more compound lie-to-stand movements were recorded than stand-to-lie movements.

The automated algorithm correctly identified 78% of the walking compound movements. Four of the compound walking movements that were not detected as such contained a period of activity of duration of less than 3 s (the duration threshold for the walking identification algorithm) that was not classified as walking. The other eleven compound walking movements that were not detected as such contained a period of activity that was not identified as cyclic activity and so was not classified as walking. In all of these cases, the other period of activity contained between the two button presses was identified as walking and so was identified as the directed activity by the automated algorithm.

The automated algorithm correctly identified only 44% of compound transitions between standing and lying. This was due to the difficulty of identifying transitions between sitting and standing in this context. After performing a lie-to-sit transition, the subject sat upright rather than reclining. She remained sitting only briefly before performing the sit-to-stand transition. As a result, the classifier could not determine whether the subject was sitting or standing during the period of sitting, and this made it very difficult for the classifier to distinguish between a sit-to-stand transition and other movement in this context. On all of the occasions on which a compound transition was not detected, the sit/stand transition was not identified and the sit/lie transition was identified as the directed activity.

The results of the automated classification are summarised in table 8.10. In this study 2010 (97.9%) of the 2054 directed activities were correctly identified. The errors were as follows.

- On 1 occasion the system failed to identify either of the two periods of activity that were contained between two button presses as the expected directed

Iterations of routine ($N = 6$)	417
Directed activities	2054
Directed rest periods	2451
Total activities detected	2609
Extra periods of activity detected	555
Compound movements	103
Activities correctly classified	2010 (97.9%)
Activities incorrectly classified	44 (2.1%)

Table 8.10: Characteristics of collected data and classification results from study 4D.

activity.

- On 5 occasions an extraneous period of activity was incorrectly determined to be the directed activity.
- On 35 occasions the system did not detect a compound movement as being such, but rather identified one part of the movement as being the complete movement.
- On 3 occasions the system erroneously identified a compound movement.

8.3.5 Statistical Analysis of Directed Movements

Mean, median, standard deviation, minimum, maximum and range were computed for each of the parameters listed in table 7.1 for each subject and across all subjects in each study. The descriptive statistics across all subjects in each of the three cohorts are tabulated in appendices D–F. These appendices also contain boxplots of tilt angle, SMA, x, y and z-axis acceleration means and ranges, and magnitude acceleration vector, ρ, mean and range, plotted for each of the 11 movements across all subjects in the cohort, for each of the three cohorts of studies 2D, 3D and 4D. Boxplots showing the vertical tilt angle and the SMA for each of the 11 directed movements for each subject for studies 2D and 4D are also included in the appendices.

Consistency of Results

The tables in appendices D–F give the means and standard deviations for every parameter for each cohort. In each subject cohort, the results obtained for each parameter for each subject were similar in each repetition of the directed routine.

	study 2D		study 3D		study 4D	
	duration	SMA	duration	SMA	duration	SMA
	(s)	($\times 10^{-3}$ g)	(s)	($\times 10^{-3}$ g)	(s)	($\times 10^{-3}$ g)
resting	N/A	73	N/A	57	N/A	58
stand-to-sit	4.4	284	3.4	345	4.8	284
sit-to-stand	2.6	278	3.9	334	3.5	257
walk	N/A	379	N/A	433	N/A	282
stand-to-lie	6.1	376	5.7	388	6.4	323
lie-to-stand	6.6	381	5.5	360	6.0	262

Table 8.11: Mean values for some parameters from the directed studies.

In study 3D, in which the subject remained healthy throughout the study and performed 62 iterations of the routine, the standard deviation in the parameter values was less than 5% of the range for the parameters. In studies 2D and 4D the parameter values were also similar between subjects within the cohort.

Mean Values of Selected Parameters

In study 2D, the average step rate (mean $\pm$ standard deviation) across all subjects in study 2D was 1.85 ± 0.30 Hz (measured by the Fourier transform method). The mean step rate variability for each period of walking (measured by the template matching method) was 0.25 s. In study 3D, the mean step rate for the subject was 1.55 ± 0.12 Hz and the mean step rate variability for each period of walking was 0.23 s. In study 4D the average step rate across all subjects was 1.77 ± 0.25 Hz, as estimated by the Fourier transform method and the mean step rate variability was 0.3 s.

Small amounts of postural sway were detected for all subjects during the 30 s period of quiet standing. In study 2D the mean frequency of the sway across all subjects was 0.27 Hz with an average interquartile range of 6×10^{-3} g in the magnitude acceleration vector. In study 3D the mean frequency of the sway was 0.25 Hz with an average interquartile range of 15×10^{-3} g in the magnitude acceleration vector. In study 4D the mean frequency of the sway across all subjects was 0.28 Hz with an average interquartile range of 8×10^{-3} g in the magnitude acceleration vector.

The mean values for some of the other significant parameters across all iterations of the routine for all subjects in each cohort are given in table 8.11.

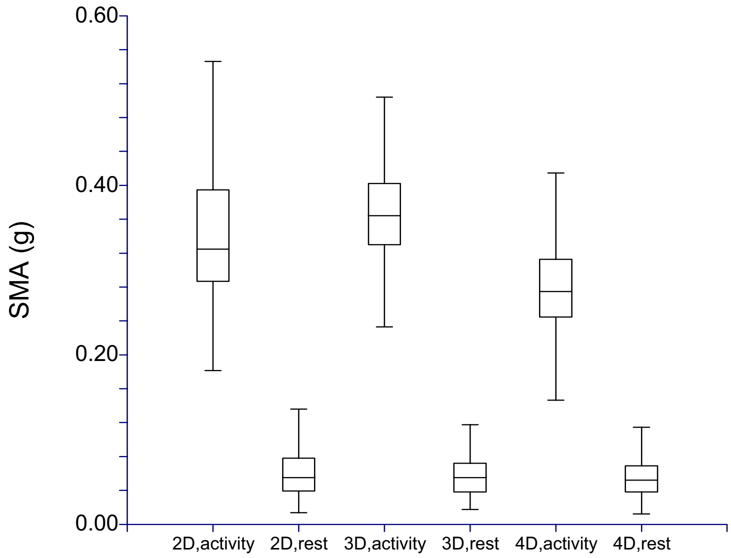


Figure 8.4: Boxplot showing the SMA values for periods of activity and periods of rest for studies 2D, 3D and 4D.

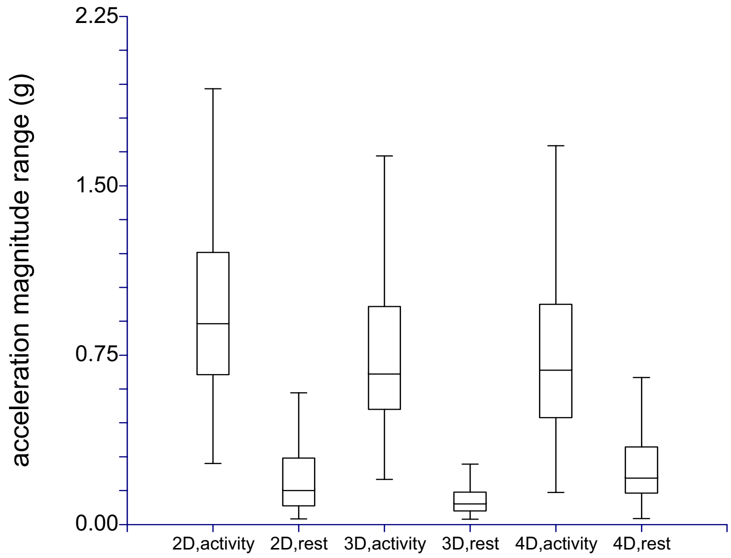


Figure 8.5: Boxplot showing the acceleration magnitude range values for periods of activity and periods of rest for studies 2D, 3D and 4D.

Differences Between Activity and Rest

Figures 8.4 and 8.5 show the values of the SMA and acceleration magnitude range during periods of rest and activity for each of the three studies, 2D, 3D and 4D. In each case, the values are taken across all iterations of the routine performed by all subjects. In each study there was a significant difference in mean values of SMA and acceleration range between the periods of activity and the periods of rest. Within each study, the average value of each directed period of activity differed significantly from the average value of each directed period of rest, and vice versa, with one exception. This exception occurred in study 2D, movement 11 (when the subjects were standing after performing a lie-to-sit transition). The subjects exhibited significantly more movement during this period of rest than in any period of rest and the SMA and the acceleration ranges were comparable to those obtained during activity (this can be seen in the data presented in appendix D). There are several possible causes for the difference in movement levels between this period of standing and the other periods of standing:

- Subjects may have pressed the button early, before they had fully completed the lie-to-stand transition, and so some activity at the end of the transition was included in the period of standing.
- Subjects may have taken several seconds to fully regain their standing balance after lying down and this may have led to more movement at the start of the standing period.
- Subjects knew that this was the last required action and this may have led to some restlessness as they waited for the testing to finish.

Further study would be required to determine the actual cause of the difference.

Differences Between Postural Orientations

In all three studies statistically significant differences were obtained between lying and other postures in the mean x-axis accelerations and in the tilt angles. Statistically significant differences were also found in all three studies between sitting and standing in the mean x-axis acceleration and in the tilt angle. Both the mean tilt angle and the mean x-axis acceleration were greatest when subjects were lying and least when subjects were standing. In studies 2D and 3D, statistically significant differences between all three postural orientations were found in the mean y-axis accelerations, but in study 4D no significant differences were found between

movements	study	1 (stand)	3 (sit)	5 (stand)	7 (stand)	9 (lie)
11 (stand)	2D	***	***	***	***	***
	3D	*	***	-	-	***
	4D	-	***	-	-	***
9 (lie)	2D	***	***	***	***	
	3D	***	***	***	***	
	4D	***	***	***	***	
7 (stand)	2D	-	***	-		
	3D	*	***	*		
	4D	-	***	-		
5 (stand)	2D	-	***			
	3D	-	***			
	4D	-	***			
3 (sit)	2D	***				
	3D	***				
	4D	***				

Table 8.12: A comparison of mean x-axis accelerations for different postural orientations for studies 2D, 3D and 4D. The postural orientations listed in the left column are being compared to the postural orientations listed in the top row for each of the three studies. These postural orientations were taken from the daily routine of 11 directed movements. The table indicates pairs of postural orientations for which the mean x-axis acceleration is significantly different. $*$ indicates $p < 0.05$, $**$ indicates $p < 0.01$, $***$ indicates $p < 0.001$ and $-$ indicates that there was not a statistically significant difference in mean values.

any postural orientations in the y-axis acceleration. The results are summarised in tables 8.12, 8.13 and 8.14.

Detection of Walking

Each period of detected activity was tested to determine whether or not it was a period of walking. Three techniques for determining whether the movement was cyclic were tested. These were (i) the algorithm based on the Fourier transform; (ii) the template matching algorithm applied to the signals from all three axes with a majority vote at the end; and (iii) the template matching algorithm applied only to the z-axis signal. The complete walking detection algorithm was also applied to detect periods of activity. The results of the walking detection are summarised in table 8.15.

In study 2D the Fourier transform algorithm performed best in terms of identifying periods of walking. This method correctly identified 64 of the 65 periods of walking, compared to 37 instances detected by the template matching algorithm

movements	study	1 (stand)	3 (sit)	5 (stand)	7 (stand)	9 (lie)
11 (stand)	2D	-	***	-	-	***
	3D	-	***	-	-	***
	4D	-	-	-	-	-
9 (lie)	2D	***	***	***	***	
	3D	***	***	***	***	
	4D	-	-	-	-	
7 (stand)	2D	-	***	-		
	3D	-	***	-		
	4D	-	-	-		
5 (stand)	2D	-	***			
	3D	-	***			
	4D	-	-			
3 (sit)	2D	***				
	3D	***				
	4D	-				

Table 8.13: A comparison of mean y-axis accelerations for different postural orientations for studies 2D, 3D and 4D. The postural orientations listed in the left column are being compared to the postural orientations listed in the top row for each of the three studies. These postural orientations were taken from the daily routine of 11 directed movements. The table indicates pairs of postural orientations for which the mean y-axis acceleration is significantly different. $*$ indicates $p < 0.05, **$ indicates $p < 0.01, ***$ indicates $p < 0.001$ and $-$ indicates that there was not a statistically significant difference in mean values.

movements	study	1 (stand)	3 (sit)	5 (stand)	7 (stand)	9 (lie)
11 (stand)	2D	***	***	***	***	***
	3D	-	***	-	-	***
	4D	**	***	***	***	***
9 (lie)	2D	***	***	***	***	
	3D	***	***	***	***	
	4D	***	***	***	***	
7 (stand)	2D	-	*	-		
	3D	**	***	*		
	4D	-	***	-		
5 (stand)	2D	-	**			
	3D	-	***			
	4D	-	***			
3 (sit)	2D	**				
	3D	***				
	4D	***				

Table 8.14: A comparison of mean tilt angles for different postural orientations for studies 2D, 3D and 4D. The postural orientations listed in the left column are being compared to the postural orientations listed in the top row for each of the three studies. These postural orientations were taken from the daily routine of 11 directed movements. The table indicates pairs of postural orientations for which the mean tilt angle is significantly different. $*$ indicates $p < 0.05, **$ indicates $p < 0.01, ***$ indicates $p < 0.001$ and $-$ indicates that there was not a statistically significant difference in mean values.

Method	**walking identification rate**		
	study 2D	study 3D	study 4D
Fourier transform method	98.5%	100%	85.8%
template matching method, 3 axes	56.9%	100%	83.9%
template matching method, z-axis	75.4%	100%	86.7%
complete walking detection algorithm	98.5%	100%	99.5%

Table 8.15: Performance of the three walking detection algorithms.

applied to all three axes and 49 instances detected by the template matching algorithm applied only to the z-axis signal. The one period of walking that was not detected by the Fourier transform method was not detected by either of the other methods and so application of the complete walking detection algorithm led to a true positive classification rate of 98.5% (64 of 65 instances correctly detected). In study 3D all three walking algorithms detected every instance of walking. In study 4D the Fourier transform method identified 85.8% of walking activity with no false positive detections. The template matching algorithm applied to all three axes correctly identified 83.9% of walking activity. When the template matching algorithm was applied to the z-axis acceleration alone it correctly identified 86.7% of walking activities. Application of the complete walking detection algorithm led to a true positive classification rate of 99.5% (413 of 415 instances correctly detected). None of the methods resulted in any false positive classifications in any of the studies.

The average step periods were then determined for each of the periods of walking that were detected by all three methods. In study 2D the Fourier transform method consistently measured the single step period, whereas the template matching method consistently measured the cycle time (double step period). When this difference was corrected for (by halving the estimates obtained from the template matching method) the average difference (mean $\pm$ standard deviation) in the estimated average walking period between the first two methods was 5.4 ± 2.7 samples. (Given a sampling rate of 45 Hz, this is equivalent to an average difference of 0.12 ± 0.06 s between estimates from the different methods.) In study 3D, all three methods consistently measured the single step period. The mean difference ($\pm$ standard deviation) in estimated average walking period between the first two methods was 2.39 ± 1.75 samples. In study 4D the Fourier transform method consistently measured the single step period in this cohort, whereas the template matching method consistently measured the cycle time. When this difference was corrected for (by halving the estimates obtained from the cross correlation method) the difference (mean $\pm$ standard deviation) in the estimated average walking period between the first two methods was 8.77 ± 8.01 samples. The results are summarised in table 8.16.

Longitudinal Tracking of Parameters

Study 2D Insufficient data were collected from each subject in study 2D for any longitudinal tracking to be undertaken.

	study 2D	study 3D	study 4D
method 1	24.99 ± 4.86	29.22 ± 1.87	25.90 ± 3.22
method 2	21.58 ± 4.76	29.67 ± 5.04	24.58 ± 5.66
method 3	23.57 ± 5.68	28.51 ± 3.12	21.50 ± 5.56

Table 8.16: Average step period (mean $\pm$ standard deviation) in samples for subjects in each study, computed by each of the three methods. Method 1: Fourier transform method; method 2: template matching on 3 axes, and method 3: template matching on the z-axis. One sample corresponds to $\frac{1}{45}$ s

Study 3D Slight to moderate correlations were found between day of testing (from the beginning of the study period) and

- the duration of the stand-to-sit movement (Spearman-rank $r = -0.320$);
- the SMA of the stand-to-sit movement ($r = -0.422$);
- the SMA of the sit-to-stand movement ($r = -0.288$);
- the SMA when sitting ($r = -0.389$); and
- the tilt angle when sitting ($r = -0.534$).

There was no change in the mean value of any of the other parameters over time.

The time-based correlations that were detected suggest a learning effect that occurred as the study proceeded. At the start of the study, the subject was less sure of the sequence of events and as a consequence, needed to move into position before sitting down, remained sitting upright during the sitting phase, and moved more vigorously than normal. As the study progressed the subject became more accustomed to the routine and carried out the movements more promptly, resulting in a decreased stand-to-sit duration. The subject also became more relaxed, and this led to more natural movements with a reduction in SMA and an increase in tilt angle when sitting.

Study 4D A learning effect was also evident in the signals recorded from the directed routine in this cohort. As subjects became more familiar with the procedure, the signals became smoother, with less extraneous movement. This effect is illustrated in figure 8.6, which shows the traces obtained from subject 1 on the first day of use (figure 8.6a) and five days later (figure 8.6b). It took 1–2 weeks of using the system before subjects became comfortable with the procedures. This agrees with feedback provided by the subjects, which changed over the course of the study.

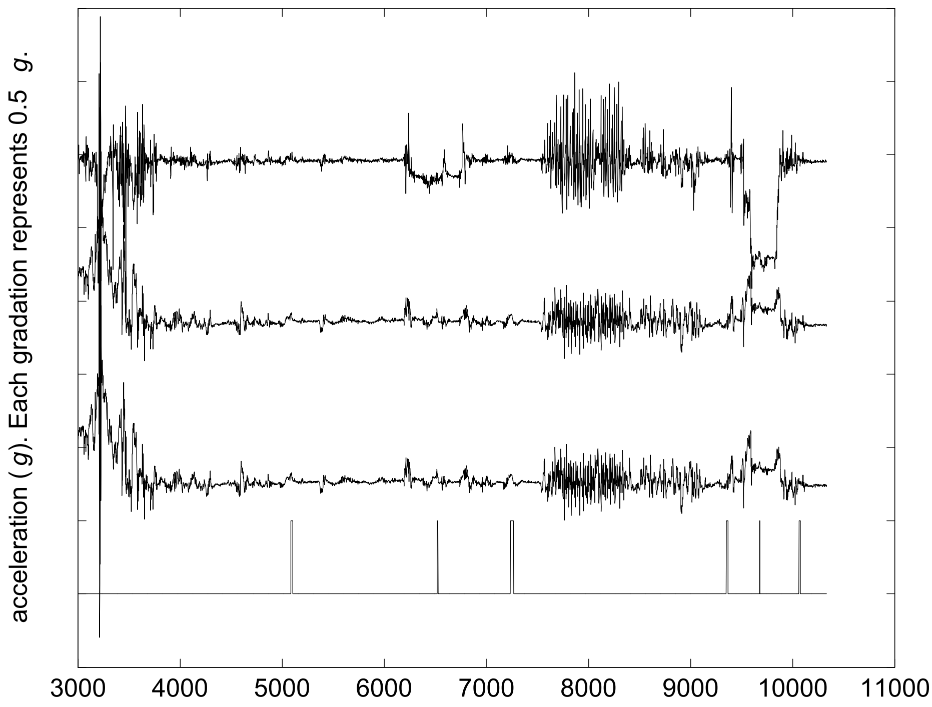
At the start of the study all subjects reported being nervous and were concerned that they would not carry out the routine correctly. However, after two weeks all subjects reported that they had no difficulty in carrying out the directed routine and at the end of the study all of the subjects reported that they found the directed routine very simple and straightforward. Regardless of this learning effect, all of the signal traces were included in the analysis.

Each of the parameters of movement was tested for correlation with day of testing (from the beginning of the study period) and with the daily and weekly self-reported health status. Although there was a learning effect present over the first 1–2 weeks for each subject, there was no change in the mean value of any of the parameters over time and no correlations were found between day of testing and any of the measured parameters. No correlations were found between self-reported health status and any of the measured parameters. This suggests that the functional status of each of the subjects remained stable throughout the study period. This is in agreement with the self-reported health status from the weekly questionnaire, and the assessments performed at the beginning and end of the study, which showed no change in functional status over the study period.

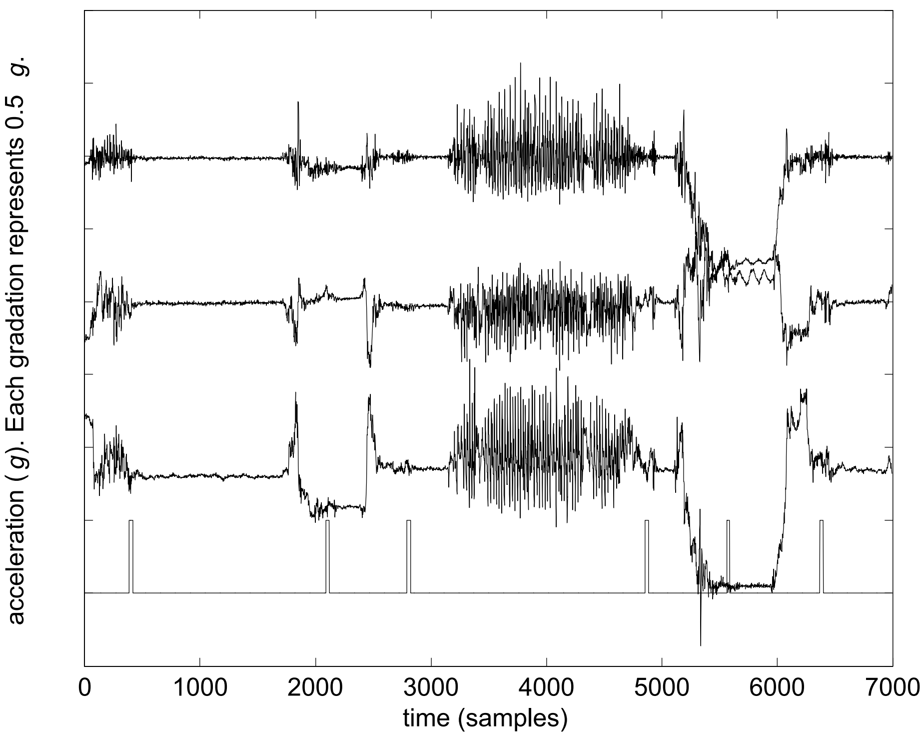
Effects of Supervision and Environment

The presence of supervision had no noticeable effect on the manner in which the directed routine was performed. In study 2D the activity detection algorithm correctly identified every period of directed activity as activity and every period of directed rest as rest. This indicates that the activity detection algorithm that was developed and evaluated in supervised laboratory studies was appropriate for use in an unsupervised laboratory setting with a similar cohort of subjects, and that the same algorithm parameter values (for parameters th, w, and n) which were optimal in the supervised environment were also suitable in the unsupervised environment. Similar results were achieved in study 3D, in which the same algorithm with the same parameter settings was used in a supervised home environment, and so it can be concluded that this algorithm is also suitable for use in a home setting.

The parameter values obtained in studies 2D and 3D were similar to those obtained in the supervised laboratory studies. This indicates that the algorithms developed in chapter 6 are also suitable for use in unsupervised and home settings with a similar subject cohort. Moreover, the parameter values obtained in studies 2D and 3D were similar to each other. Three statistically significant differences were detected in parameters of two different movements between the subject groups. The home subject of study 3D recorded a statistically greater SMA and a more



(a)



(b)

Figure 8.6: An example of learning on the daily routine signal in study 4D. (a) the trace obtained from subject 1 on the first day of use, and (b) the trace obtained from subject 1 five days later. The second trace is smoother than the first and contains less extraneous movement and pauses during activities. The three signals have been shifted vertically to allow them to be seen more clearly. From top: z-axis, y-axis, x-axis, and button press.

upright posture than the laboratory subjects during the stand-sit-stand phase of the routine, and a lower SMA during the final stand phase ($p < 0.001$). There was also a statistically significant difference in the duration of the lie-to-stand transition ($p < 0.001$), with the home subject carrying out the activity more quickly than the subjects in the laboratory. The higher SMA recorded in the study 3D subjects during the final period of standing is consistent with the earlier finding that these subjects moved about more during this period of standing than in the earlier periods of standing. As discussed, this may have been due to a preemptive pressing of the button before the lie-to-stand transition was completed, or due to anxiety to complete the test. The home subject did not demonstrate this characteristic. The finding that the home subject carried out the lie-to-stand transition more quickly than the subjects in the laboratory was to be expected as the home subject lay on a bed, whereas the CHI subjects lay on the floor.

In every study, the SMA alone could be used to distinguish between rest and activity, and tilt angle alone could be used to distinguish between upright and lying postures. Moreover, there was found to be a statistically significant difference in the acceleration signals on the x- and z-axes between sitting and standing postures. All of these results are in agreement with the results found in the supervised laboratory tests.

Effect of Age

The parameters obtained in study 4D were compared to those obtained in study 2D. Since it was established that neither the presence or absence of supervision, nor a laboratory or a home setting affected the way in which the directed routine was performed, this allowed a comparison between the manner in which the directed routine was performed by a young cohort and the way in which it was performed by an elderly cohort.

The postural orientations of both subject groups were similar for each posture. The activity durations were also similar between the two groups. The mean ($\pm$ standard deviation) time taken for the sit-to-stand transition was 2.6 ± 0.8 s for the younger cohort, and 3.5 ± 1.3 s for the elderly cohort. This difference was statistically significant ($p < 0.001$), but there were no other significant differences in activity durations.

The elderly group recorded lower SMA values for all activities but the stand-to-sit transition ($p < 0.001$). They also recorded greater SMA values during the 30 s stand and during the lying period ($p < 0.001$), and a lower SMA value during the final standing period ($p < 0.001$). Consistent with this, the elderly cohort recorded a smaller acceleration range during activity than the younger cohort and a greater acceleration range during periods of rest ($p < 0.01$), except in the last period of standing when they recorded a significantly smaller acceleration range ($p < 0.001$). As these results were obtained consistently for almost every movement, it can be concluded that the younger cohort were able to remain more still than the older cohort during rest periods, and moved more vigorously during periods of activity than the elderly subjects, although there was no difference in the amounts of postural sway measured in the two groups.

There was no difference between the cadence or the variability of the gait between the two groups.

8.3.6 Discussion

The values of the parameters that were extracted from the routines showed consistency within subjects and between subjects. This indicates that the waist mounted TA is a reliable instrument for unsupervised monitoring of movement. Other studies have demonstrated a high test-retest reliability when using accelerometers attached to the head and trunk for posture and activity analysis [92, 169]. The current study demonstrates a similar reliability when the TA unit is attached at the waist and used in an unsupervised setting. The values of the parameters that were extracted are also comparable to the values that would be expected, based on the literature. For example, normal sit-to-stand transition times are around 1–3 s [121, 122], and typical step rates during walking are around 1.5–2 steps per second [56, 70, 87]. The sit-to-stand and stand-to-sit transition times obtained in this study were at the high end of those expected from the literature, although they are well within the ranges reported by Kralj *et al.* [128] and are substantially less than those times reported for subjects with disability [172]. In the current work, the start and stop of each activity were defined in terms of the magnitude of the acceleration generated by the subject and encompassed the entire period over which the body was not at rest. This definition of start and stop differs from that used in biomechanical studies in which the start and stop of the activity are defined in terms of reaction forces and body position, and the defined transition can start after the body has begun moving and end before the body has completely stopped moving. This led to slightly longer timing results for activities using this TA system when compared to results presented in the literature. The stand-to-sit transition times were also lengthened slightly in studies 2D and 4D by subjects needing to move into position (for example, needing to turn around) in order to sit down. The subject in the supervised study 3D always commenced the period of standing (movement 1) in a position from which she could sit directly down, although she was given the same instructions as the other subjects, and this resulted in shorter measured stand-to-sit transition times for this subject.

There were no significant differences in the results obtained between the 2D and 3D studies, except that the unsupervised laboratory cohort exhibited a greater level of movement during the final period of standing. In each study, the results indicated that activities and postures could be identified using the same methods and algorithmic parameter settings that were applied to the supervised laboratory data. The results that were obtained indicate that the methodologies and parameters developed in the supervised laboratory studies for directed movement are appropriate for monitoring of a similar subject cohort in an unsupervised setting and in the home. Moreover, the durations, tilt angles, mean acceleration values, SMA values and acceleration ranges obtained in this study were similar to those obtained in the supervised laboratory studies, which indicates that the manner of performance of the routine is basically unaffected by the presence or absence of supervision.

Study 4D collected data from a cohort of elderly subjects. When these data were compared to those of the younger subjects it was found that the elderly subjects performed the sit-to-stand transition more slowly, exhibited more movement while resting and recorded lower SMA values for all activities but the stand-to-sit transition than the younger subjects. All of these differences indicate changes consistent with normal ageing [105, 122, 166, 182, 234], and are the result of age related reductions in body strength and postural control.

Although postural sway was recorded during quiet standing for every subject, the levels of sway that were detected were very slight ($6–15 \times 10^{-3}\ g$) compared to those achieved by the subject who performed the postural sway study of section 6.6.8. That subject recorded a peak-to-peak sway amplitude of over $100 \times 10^{-3}\ g$ when swaying as vigorously as possible. The mean sway frequency was similar in both studies—around 0.26 Hz, and this is in agreement with values reported in the literature [240].

In addition to the parameters that were recorded, the amount of extraneous activity recorded during the directed routine and the presence of compound movements may also prove to be clinically useful. Periods of extraneous activity were more common among the elderly subjects than among the younger subjects. The amount of extraneous activity following directed activity, and during standing, are parameters that warrant further investigation. The amount of movement carried out by a subject immediately following a sit-to-stand or a lie-to stand transition may provide a measure of the dynamic balance capabilities of the subject. For example, if a subject needs to take several steps after standing up in order to regain balance it may be an indicator of poor balance. The same may be true of movement during quiet standing.

Compound movements were also more common among the elderly cohort than among the younger cohorts. Further work is required to determine whether compound movements become increasingly prevalent with increasing frailty or illness, but if so, then the time-spread of energy expenditure during the activity may be a useful parameter in characterising the activity, particularly for transitions (i.e. was the subject able to complete the transition as a single movement, or were several stages of movement required?). Future work should investigate the utility of these parameters.

One of the reasons for introducing a directed routine was so that data could be obtained from known movements. In spite of the presence of extraneous activities, the use of the directed routine with button presses acting as markers resulted in very high classification accuracies (at least 97.8% for all activities in every study). This performance far exceeds the classification rates that have been achieved in the classification of free movement, which is discussed in section 8.4. It also ensures that the movements are performed in the same way so that there is as little uncontrolled variation as possible in the performance of the movements over time.

In these studies, during the directed routine, subjects were asked to remain sitting and lying for 10 s. This value was chosen as a trade-off between compliance and data collection, because in directed laboratory studies subjects expressed impatience if the routine took too long. However, in the unsupervised studies, and particularly in study 4D, subjects often spent several seconds getting comfortable in the new posture, and this reduced the amount of time spent in the directed periods of quiet rest. Time constraints were a less important factor for the elderly cohort, and the time spent in sitting and lying could probably be increased to 30 s without increasing the inconvenience to the subject. This would increase the time over which the average parameter values were measured during these periods, by a factor of 3, and so increase the accuracy of the measurements. The standing period should not be increased from 30 s, as several of the elderly subjects found that this was a long time to be standing quietly and were glad to sit down at the end of it. For frail or ill subjects, this period of standing would be more difficult. Moreover, 30 s appears to be a sufficient time in which to collect information on balance and sway [112, 139, 162] so a longer period is not required.

There were a substantial number of extraneous activities performed in the directed routine, particularly by the elderly subjects. Many of these periods of activity occurred when subjects moved the TA unit in order to press the button. The periods of extraneous activity made it more difficult to identify the actual directed activities. A period of 5 s was allowed for the directed transition activities before the instruction to press the button was given. This led to a situation in which subjects would complete the transition and almost immediately reach to press the button. Increasing the period allowed to 10 s would increase the spacing between the directed activity and extraneous activity due to button press, which would add a clear period of rest of at least five seconds after the directed activity and this would make it easier to identify the directed activity.

This would require a slight modification of the instructions. For example, the instruction, “Please sit down” would need to be modified to “Please sit down and then remain sitting quietly” to ensure that the subject understood the requirement for quiet rest at the completion of the activity. The requirement for quiet rest was not specifically mentioned in the instructions that were given due to a decision to keep the instructions as simple as possible. During training it was ensured that all subjects understood that they were required to stand, sit and lie quietly during the periods of rest. However, it may be beneficial to specifically mention during the directed routine that the subject should remain still during the rest periods.

The walking algorithms that were presented in section 6.8 were tested on the data obtained from the sequences of directed movement. This allowed a direct comparison of the different methods on walking that was not strictly regulated. In study 2D the Fourier transform method performed substantially better than the template matching methods, but in studies 3D and 4D there was little difference between the methods. The most likely reason for the difference in performance of the template matching algorithm in study 2D compared with the other studies is that the subjects of study 2D changed their walking style during the period of walking whereas the subjects who performed the routine at home did not. In the home subjects were able to carry out the routine uninterrupted and perform the walk along a familiar route that was free of obstacles. On the other hand, study 2D was carried out in an office environment during business hours. Subjects may have been interrupted by colleagues during the period of walking, or needed to avoid obstacles or other people moving along the corridor. This would lead to subjects changing their gait styles. The template matching algorithm depended on each step being carried out in the same way. If the template matching algorithm chose a template from a period in which the subject’s gait was affected by interruption then it may not have found sufficient repetitions of the template in the signal for it to declare the period of activity to be cyclic. Better results were obtained in the home studies because subjects maintained a more regular gait.

If this reasoning is correct, then the template matching algorithm could be improved by using a specific, rather than a random, template. A template could be chosen for the subject from a sample of free walking and then this template used in the analysis of other periods of walking.

No benefit was found in using the three-dimensional template matching technique over the z-axis alone. Moreover, in all of these studies, the Fourier-based method performed as well as the pattern-matching techniques. This is because all of the subjects involved in these studies exhibited normal, regular gait. The Fourier based method is expected to perform less well in the presence of irregular or pathological gait where a clear frequency peak is not present. In these cases, the template matching technique is expected to be more effective. Future work should involve the identification and analysis of abnormal gait with a TA using automated algorithms.

The complete walking detection algorithm identified all of the periods of walking in study 3D and all but one period in studies 2D and 4D. In study 4D this gave a better performance than either the Fourier transform method or the template matching method alone. It also generated no false positives, so from this study it can be concluded that the sequential use of classifiers improves the true positive rate of walking identification without having a detrimental effect on the false positive rate.

Each of the three methods for measuring the mean step rate gave a slightly different value. This is to be expected as the average was computed in a different way in each case. Moreover, it would be expected that several applications of the template matching method would give slightly different values, depending on the template that was selected. However, each of the estimates of mean step rate was within one standard deviation of the other mean estimates (table 8.16).

The Fourier transform method consistently measured the single step rate, whereas the template matching method sometimes identified the single step rate and sometimes identified the double step rate. When there was sufficient regularity and symmetry between left and right steps then the template matching algorithm found that both left and right steps matched the template signal sufficiently well and the single step rate was measured. When there was not sufficient symmetry then the template matching algorithm only matched the steps performed by the same foot that the template was taken from and this resulted in a measurement of the double step rate.

In study 4D all of the subjects remained relatively healthy throughout the study and no changes in health or functional status were measured between the start and the finish of the study. The finding that there were no trends in the measured parameters over time for any of the subjects was consistent with this. The next stage of work requires a field trial to test the hypothesis that longitudinal trends will be found in the measured parameters when the health status of the subject changes over time (refer to section 9.6).

In these studies the button on the TA unit was used as an indicator that an activity was completed. This methodology also provides a convenient means of regularly testing the performance of the button, which can be used as a personal alarm during periods of free movement.

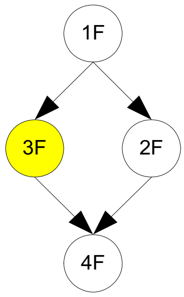
In these studies all subjects carried out the same directed routine. The movements that were tested were all movements basic to independent living. However, in cases where a subject with a specific condition is being monitored the directed routine could and should be customised to monitor movements particular to the needs of the subject.

8.3.7 Conclusion

The studies of directed movement that were carried out in supervised and unsupervised laboratory and home settings demonstrated that the TA system can be easily used by subjects, both young and elderly. The high degree of consistency between subjects in different studies in the values of the parameters extracted from the routines indicates that the manner of performing the routine was not significantly affected by investigator supervision or by location (laboratory or home). Thus, the system that was developed using normal healthy subjects performing in a supervised laboratory environment can validly be extended for use in an unsupervised home setting.

The movements in the directed routine were automatically classified with 98% accuracy. The parameters of movement that were discussed in the previous chapter, including transition times, postural sway and walking speed were successfully extracted from the acceleration signals. The values obtained were in agreement with values obtained in other published research. When the parameters obtained from the elderly cohort were compared to those obtained from the younger cohorts, it was found that the elderly subjects took significantly longer to stand up after sitting, that they recorded significantly lower SMA values during activity, and higher SMA values during rest.

8.4 Supervised Home Study of Free Movement (study 3F)



8.4.1 Introduction

One 28 year old, healthy female subject was provided with a TA system for three months. The subject was asked to wear the TA device whenever she spent at least half a day at home during that period. She was asked to keep a diary to record her movements during these periods.

8.4.2 Use

During the three month period for which the subject had the TA system, she wore the TA during the day on fifteen separate occasions and kept a diary record on ten of these occasions. The five days on which the device was worn, but no diary record kept, were excluded from the analysis.

On five occasions, the subject's diary was insufficiently detailed for it to be of use in identifying movements. For example, the diary entry for one occasion read, "Started around 9:30. Stopped around 5. Wandered around home. Did some computing, washing, sat round and played with the dogs.". Other diary entries were extremely detailed, specifying the exact time of each movement, for example, "... 10:32:57: sat down again to write in log. 10:33:46: hung out washing ...". The five occasions for which the diary entry was not adequate were included in the calculation of the proportion of transmitted data that were received, but were not used to evaluate the classification algorithms.

Details of the ten occasions on which data were collected and a diary kept are summarised in table 8.17.

Occasion	Duration (hours)	Diary adequate?
1	7.19	yes
2	0.50	yes
3	4.77	yes
4	8.50	no
5	0.29	yes
6	1.08	yes
7	2.04	no
8	9.02	no
9	3.37	no
10	8.67	no

Table 8.17: Summary of data captured in study 3F.

8.4.3 Data Analysis

Preliminary Processing

The ten occasions on which the subject wore the TA unit and kept a diary gave 45.5 hours of movement around the home. The data capture rate was 90.09%. During this study, the subject was quite sedentary and was classified as being engaged in activity for only 11% of the time.

Movement Identification

The TA signals from the five occasions on which data were collected and a sufficiently detailed diary was kept were processed by the complete classification algorithm. The baseline values for upright tilt angles and mean SMA that were used in processing the signal were taken from the data obtained in the directed routine that was performed on the same day. No abnormally large acceleration spikes indicative of fall events were present in the data, and no such events were mentioned in the diary.

The diary entries were compared to the classifications made on the signal. For each diary entry that described a specific movement, the classifier output for the same time, plus or minus thirty seconds, was checked. If the classifier output agreed with the diary entry then the movement classification was deemed correct. If the classifier output did not agree with the diary entry then the movement classification was deemed incorrect.

In total, 98 movements were identified from the diary entries. Of these, 64 (65%) were correctly identified by the classifier. Table 8.18 shows the results broken down into basic movements of walking, sit-to-stand and stand-to-sit transitions, standing,

Walking	No. 13	Correct 12	Incorrect 1	Not Detected 0	Not Subclassified 0
	detected as other movement (x1)				
Sit To Stand	No. 20	Correct 9	Incorrect 4	Not Detected 6	Not Subclassified 1
	detected as lying to upright (x3), stand to sit (x1)				
Stand To Sit	No. 24	Correct 8	Incorrect 8	Not Detected 7	Not Subclassified 0
	detected as other movement (x3), upright to lying (x3), and sit to stand (x2)				
Standing	No. 2	Correct 0	Incorrect 0	Not Detected 0	Not Subclassified 2
	detected as upright (x2)				
Sitting	No. 23	Correct 22	Incorrect 0	Not Detected 0	Not Subclassified 1
	detected as upright (x1)				
Toileting	No. 3	Correct 0	Incorrect 3	Not Detected 0	Not Subclassified 0
	detected as lying (x3)				
General Movement	No. 13	Correct 13	Incorrect 0	Not Detected 0	Not Subclassified 0
	(cooking, washing hands, housework, wandering about) detected as upright, with walking and other movement (x13)				
Total	No. 98	Correct 64	Incorrect 16	Not Detected 13	Not Subclassified 4

Table 8.18: Classification results from study 3F. The table shows each of the movements listed in the diary, the number of occurrences, the number of occurrences that were correctly classified, the number that were misclassified, the number that were not detected, and the number that were classified at the main classification level but could not be subclassified. The second row in the table for each movement lists all of the other classifications made for that activity or posture.

sitting, toileting and general movements. The “general movements” category was introduced for activities that were described in the diary as “cooking”, “washing hands”, “housework” and “wandering about the house”. Once the signal had been classified using the classification algorithm, periods of general movement were identified. A period of signal was classified as general movement if the subject had an upright posture and was engaged in short periods of walking and periods of other activity, interspersed with brief periods of rest, and this pattern was continued for a period of at least one minute. An example is shown in figure 8.7. In this figure, the subject is washing the dishes. The period of general movement lasts for about eight minutes and during this time the subject is upright and periods of other activity are interspersed with brief periods of rest.

The number of instances of each type of movement were listed in table 8.18, together with the number of correct classifications. Instances in which the correct classification was not achieved were categorised according to the type of error. The three types were:

1. incorrect classification: the movement was classified but the classification was incorrect,

2. not detected: the activity detection algorithm failed to identify the movement. In every case this was due to an activity being combined with another activity with the result that the two distinct activities were detected as a single period of activity, and

3. not subclassified: the classification algorithm was unable to subclassify the movement beyond the basic classification.

The incorrect classifications are shown for each category below the main tabulated data. Incorrect classifications were made on 16 occasions. Nine of these incorrect classifications were made when the subject toileted. The subject recorded using the toilet on three occasions. On each of these occasions the sitting posture was recorded as a lying posture. This was due to the trousers to which the TA was attached being adjusted relative to the subject so that the orientation of the TA relative to the subject was changed, and resulted in the apparent posture being one of lying. This also led to the stand-to-sit and sit-to-stand transitions being classified as upright-to-lying and lying-to-upright transitions, respectively. The other incorrect classifications were due to sit-to-stand and stand-to-sit transitions being confused, and walking and transitions being classified as “other activity”.

Activities were not detected on 13 occasions. All of these activities were sit/stand transitions that preceded or succeeded a period of walking and in each case the subject performed the transition and the walk without pausing between the two movements. An example of this is shown in figure 8.8.

Subclassifications were not made in four instances. In three cases the classifier could not determine whether the subject was sitting or standing, and in the fourth it could not subclassify an upright-upright transition. In the other cases involving sitting and standing the parameters of duration and tilt angle proved very effective in discriminating between the two as the subject rarely remained in a quiet standing posture for more than a few seconds (other than during the routine of directed movement), and the tilt angle tended to be greater when sitting than when standing. (This can be seen in figure 8.7.) When these two parameters were used together with the classification of the preceding activity, all but one of the periods of sitting were correctly identified. The remaining period of sitting was of short duration and the subject was sitting upright and the posture could not be distinguished from a standing posture based on the signal alone. Neither of the periods of standing were subclassified from an upright posture. As was discussed in section 6.6.5, it is more difficult to identify a period of upright rest as standing than as sitting based on the signal alone. Rule-based analysis would be expected to assist in this discrimination, and this is discussed in the next section.

Heuristic Decision Making

The preceding results describe the performance of the classifier at the times for which there was a specific diary entry. There were activities identified in the signals that were not described by specific diary entries. Most of this activity occurred during periods in which the diary entries inferred that the subject was sitting, working at her desk. It may be assumed that the subject was predominantly seated, but that she moved around in order to reach different items, and possibly stood up for brief periods for the same purpose.

In this section, the signals and diary entries were compared for two of the collected data sets. These two data sets were chosen because the accompanying diary records provided the most detail of the subject's movements. The purposes of these comparisons were to observe complex, free movement patterns, to identify characteristic, complex movements, and to determine the effect of adding a heuristic overlay to the decision system on the classification accuracy.

The two data sets are shown in figures 8.9 and 8.10. The classification from the diary is shown in pink, while the output of the signal classification algorithm is

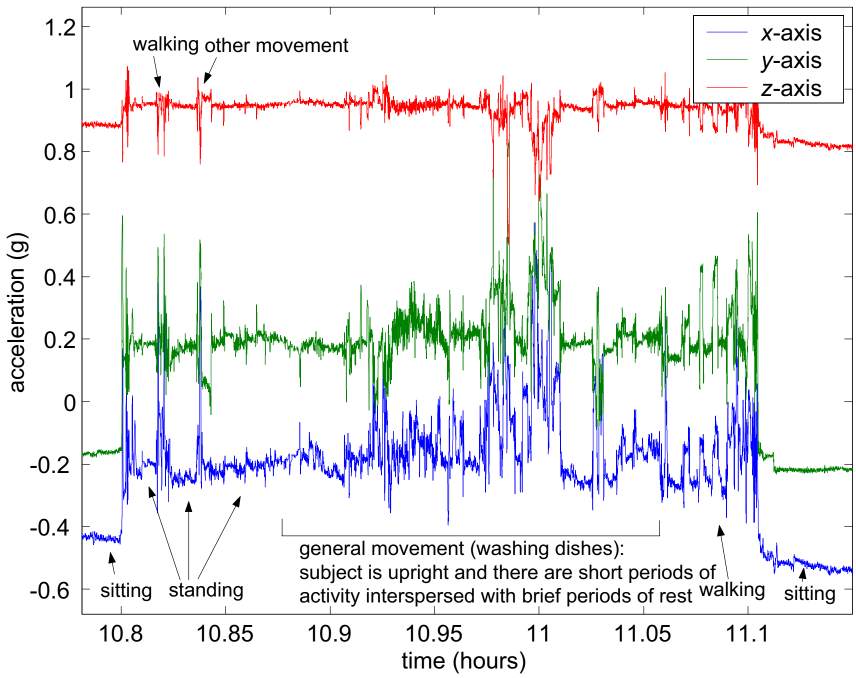


Figure 8.7: Illustration of general movement. In this figure the subject is washing the dishes. The period of general movement is composed of short periods of activity interspersed with brief periods of rest while the subject is in an upright posture.

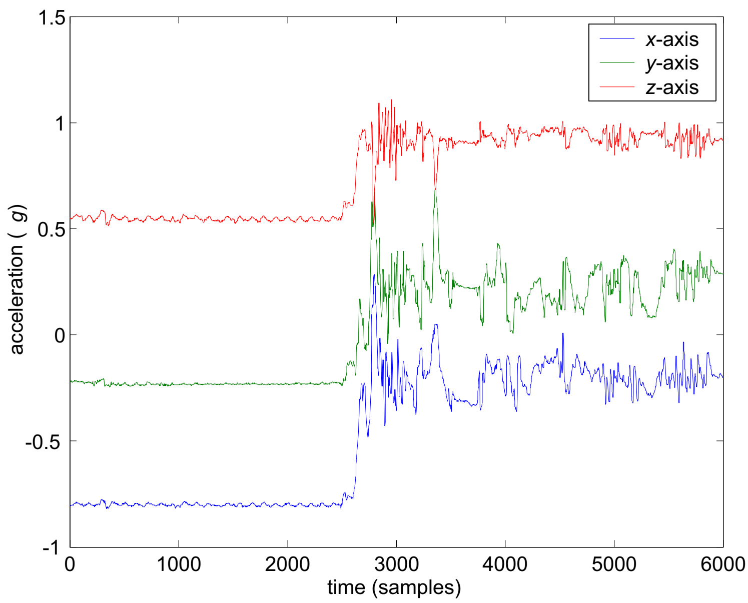


Figure 8.8: Example of an instance in which the subject performs a sit-to-stand transition and then walks away, all as part of the one movement. Note the irregularity in the gait.

	Data Set 1		Data Set 2	
	correct	incorrect	correct	incorrect
Algorithm Alone	22	29	118	34
+ Heuristic Decision	19	32	120	32

Table 8.19: Classification rates for the two data sets when the activity classification algorithm alone and the activity classification algorithm plus the heuristic overlay were applied to identify each of the movements in study 3F.

	Data Set 1		Data Set 2	
	correct	incorrect	correct	incorrect
Algorithm Alone	10	8	11	12
+ Heuristic Decision	11	7	20	3

Table 8.20: Classification rates after periods of identified activity that were not described in the diary were disregarded.

shown in black in parts (a) of the figures and the output of the heuristic decision is shown in black in parts (b) of the figures.

In the first data set, 51 distinct periods of activity and rest (identified by the activity detection algorithm) were classified. In the second data set, 152 distinct periods of activity and rest were classified. The automatically classified output was compared to the output from the diary. Each time that either the diary output or the classifier output (or both) changed, the two values were compared. If the two were in agreement then the classification was correct and was given a score of 1. If the two were not in agreement then the classification was incorrect and was given a score of 0. The scores were summed to give an overall accuracy rating. The results are given in table 8.19.

Many of the differences between the diary and the automated classification occurred because the activity detection algorithm detected activities where none were mentioned in the diary (figures 8.9 and 8.10). Some of these were classified as periods in which the subject stood up briefly, while others were classified as "other movement". It is likely that the subject moved around a little during periods of sitting at her desk, working, even though these are not explicitly mentioned in the diary. If these periods of movement are disregarded and the classification rates are computed only for the specifically mentioned periods of activity and rest then the classification rates become those shown in table 8.20.

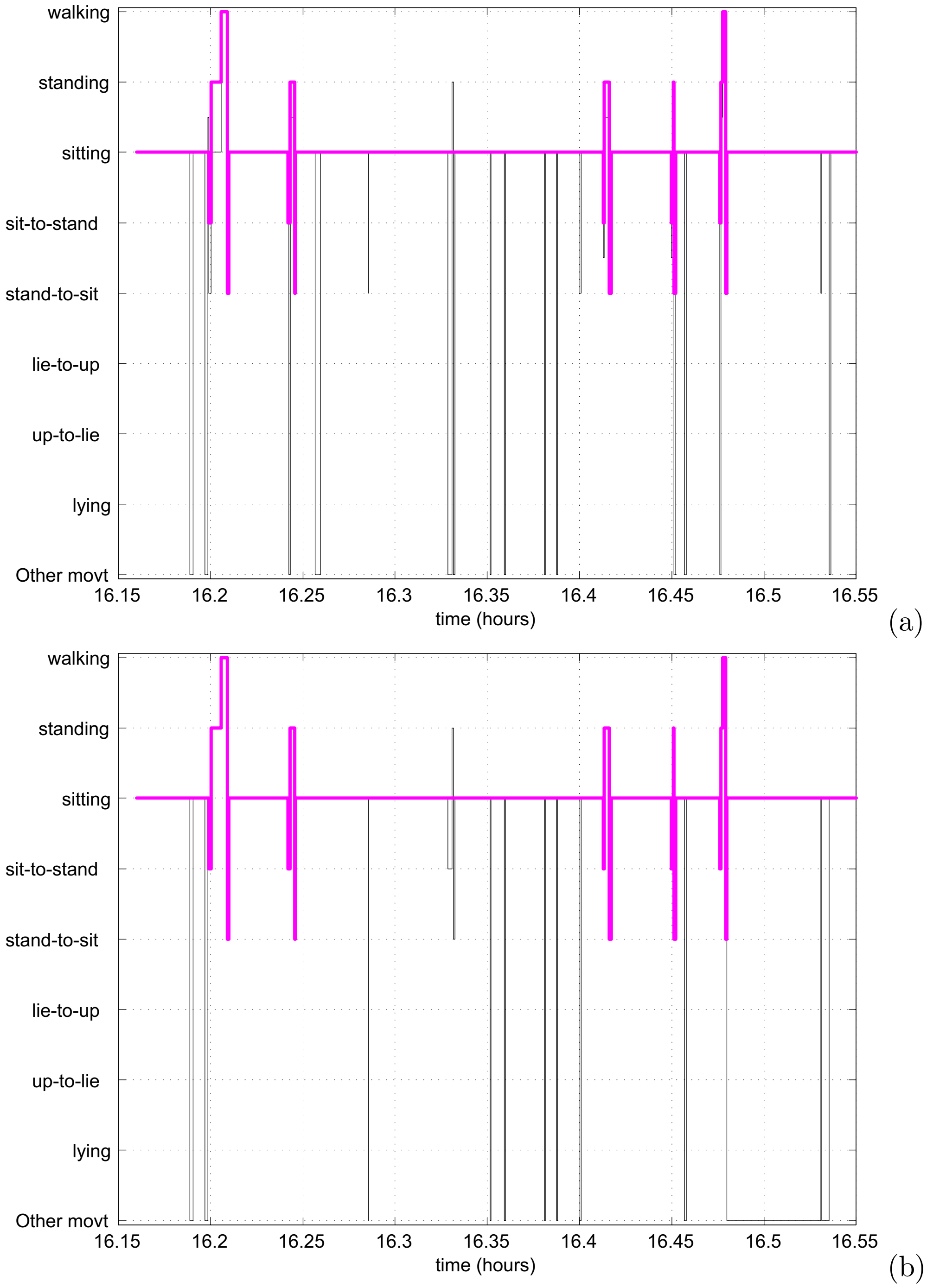


Figure 8.9: A comparison between the diary entries (pink) and the automated activity classifications (black) for study 3F (data set 1). (a) shows the output from the classification algorithm, and (b) shows the output after the heuristic rules were applied.

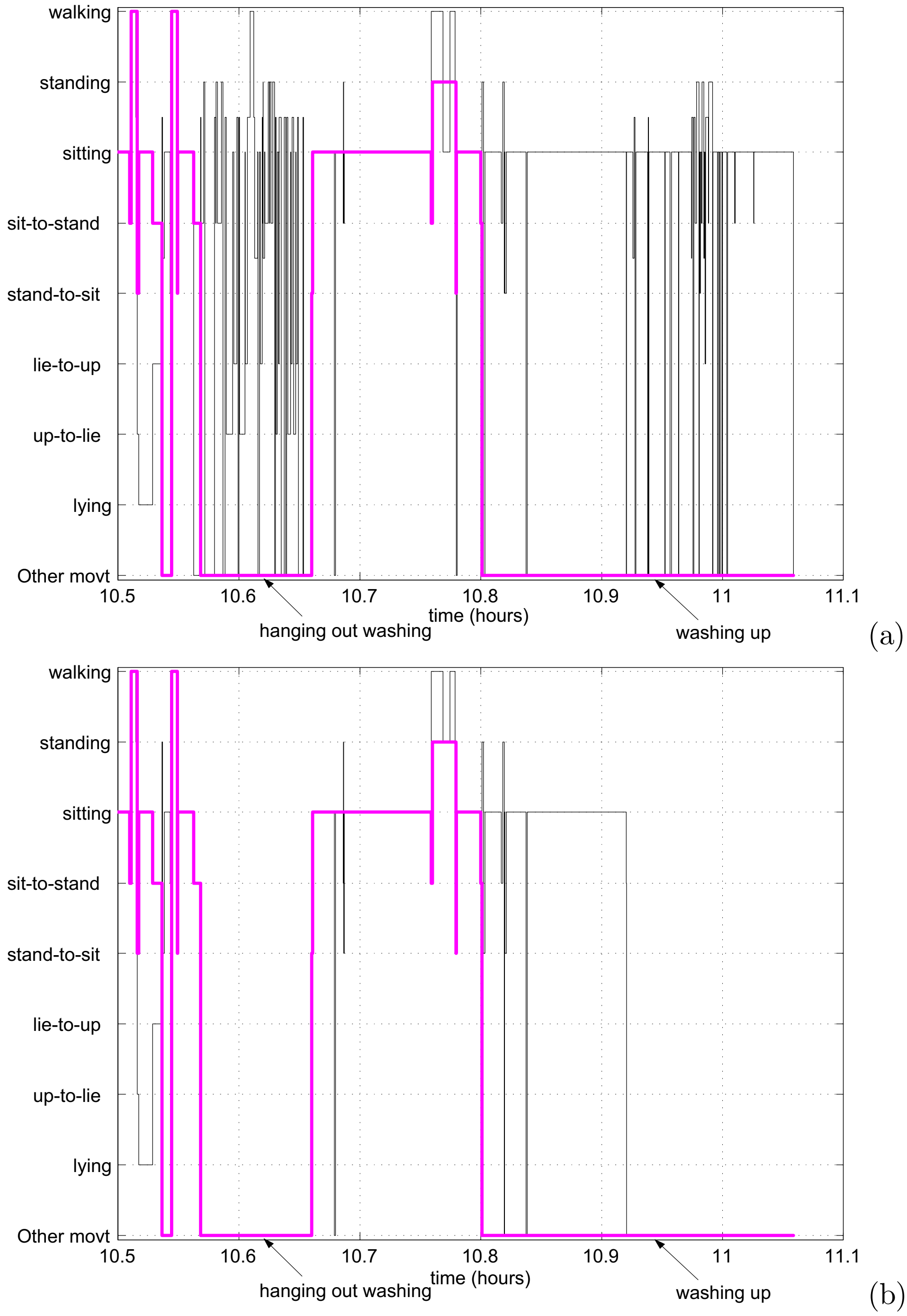


Figure 8.10: Another comparison between the diary entries (pink) and the automated activity classifications (black) for study 3F (data set 2). (a) shows the output from the classification algorithm, and (b) shows the output after the heuristic rules were applied.

8.4.4 Discussion

This study allowed the collection of a data set of free movement in which the movements were known. This enabled complex movement patterns to be identified, and the performance of the classification algorithm on free movement to be explored.

The activity detection algorithm performed reliably. It detected as activity all of the periods that the subject described as activity, and classified as rest all of the periods that the subject described as rest. Thus, the timing of events was accurately detected in the free movement, although the actual classification accuracy was much lower than for a data set of directed movement.

Classification of free movement is difficult because of the huge range of different movements that can be performed. Also, basic activities can become complex because they are performed simultaneously with another activity, or are interrupted by another movement. The irregular walking pattern shown in figure 8.8 is an example of this. The subject has no gait abnormalities but the gait in this instance is irregular because the subject did not walk directly from one location to another, but paused to look at, pick up, and put down things, and stepped around obstacles along the way. Different activities can also be joined together in the same period of activity, as was also illustrated in figure 8.8, which showed a sit-to-stand transition that was followed immediately by a period of walking, and this makes them harder to classify than a period of activity containing a single movement.

The introduction of the heuristic overlay did improve the classification accuracies for the two data sets to which it was applied (tables 8.19 and 8.20). However, the main contribution of the heuristic overlay was to ensure that the sequence of movements was consistent.

The rules that were used, both in the heuristic overlay, and in the classification algorithm (to identify falls, and to distinguish between sitting and standing) were based on assumptions of the subject's normal behaviour. These rules must be tailored for the situation in which the monitoring is to occur. In the current work the rules were designed for a housebound patient, and the rules required for other types of subjects could be quite different. For example, if a period of upright rest continued for more than 30 s, it was deemed to be a period of sitting because a housebound subject is unlikely to stand quietly for long periods.

It may be possible to identify some complex movements as a particular sequence of basic movements. For this subject, toileting is one such movement. Each time that the subject toileted, the same distinctive sequence of events—walk, stand, stand-to-lie, lie, lie-to-stand, upright + other movement (approx. 60 s)— appeared in the signal. Pattern-matching techniques (either rule-based, or neural network type) could be developed to identify such complex movements.

However, in general, identifying particular complex movements from within the signal is a difficult task as complex movements, such as preparing dinner, are not carried out in the same way on every occasion. In this study a very simple set of rules was used to categorise all extended complex movements as "general movements", a category that indicated that the subject was engaged in some daily activity rather than resting, and that the activity was not a basic movement. In terms of monitoring functional status, it is hypothesized that longitudinal tracking of parameters of movement from the directed routine together with general parameters of SMA and time spent in activity over the day will prove as valuable as a complete knowledge of the subject's daily activities, and are appreciably simpler to determine. These parameters are extracted and monitored in the unsupervised home study with the elderly subjects, and the results are described in section 8.5.

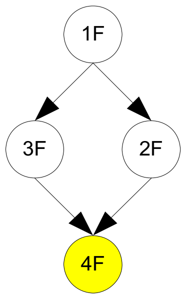
8.4.5 Conclusion

Study 3F was a feasibility study in which one healthy 28 year old subject wore the TA unit while engaged in daily activities at home. The subject found the TA unit comfortable to wear and easy to use. Data were collected on complex movements undertaken in free movement. Some of these movements, such as toileting, had a distinctive sequence that could be identified in the signal. Other movements, such as washing the dishes, had non-specific movement patterns, making them difficult to identify.

Classification was performed on the free movement, and it was found that the basic movements of standing, sitting, lying, walking and transitions were identified with an overall accuracy of 65%. Two of the data sets were studied in greater detail and a heuristic overlay was added to assist in the classification. The addition of this overlay increased the classification accuracy from 51.2% (21/41 movements) to 75.6% (31/41 movements) for these data sets.

Future work could involve investigation of complex movement patterns and further development of heuristic classification methods. However, if the purpose of the monitoring is to extract clinically significant parameters from the movement, then this can be better done through the used of the directed routine than by monitoring free movement. The directed routine has the advantages of much higher classification rates (98% compared to 65%), less processing is required, and the movements are performed in the same manner on each occasion. Then the monitoring in free movement need only collect general parameters of movement, and watch for abnormal activities.

8.5 Unsupervised Home Study of Free Movement (study 4F)



8.5.1 Introduction

The design of the unsupervised home study of directed and free movements was described in section 7.8. The study was conducted in the homes of functionally independent, elderly, community dwelling subjects. Each morning the subjects were required to attach the TA unit to the waist and carry out a directed routine consisting of sitting, standing, walking and lying. Following this, subjects were required to wear the TA unit for the rest of the day as they performed their daily activities. They were also required to complete a daily health questionnaire, a weekly health questionnaire and a falls diary. This section reports on the free movement component of the study.

8.5.2 Subjects

Six subjects participated in the study. Subject characteristics are shown in table 8.21. All subjects were over 80 years of age, healthy and living independently at home.

The Stanford Health Assessment Questionnaire disability index (HAQDI) and pain scale (HAQPS) results are presented. The HAQDI measures the ability of the subject to function in daily life. It is scored from 0 to 3, where 0 indicates no disability and 3 indicates severe functional disability. For the pain scale, subjects were asked to indicate the level of pain that they had suffered in the last week.

Subject	Gender	Age	Abode	HAQDI	HAQPS	falls risk
1	F	82	flat	0.125	1.08	mild
2	M	85	house	0.125	0	moderate
3	M	82	house	0	0.92	moderate
4	F	80	flat	0	0	mild
5	F	83	flat	0.125	2.72	mild
6	F	85	flat	0.25	0.9	moderate

Table 8.21: Characteristics of subjects participating in the unsupervised home study. Subjects lived either in a house or a flat. The Disability Index (HAQDI) and the Pain Scale (HAQPS) from the Stanford Health Assessment Questionnaire are presented. Scores range from 0 to 3. Higher scores indicate higher levels of disability or pain. The falls risk for each subject is also presented.

Subject	No. days	Mean hours/day
1	92	12.9
2	78	8.8
3	73	11
4	60	10.6
5	67	10.9
6	56	12.8

Table 8.22: Details of TA use during free living in study 4F.

The pain scale is scored from 0 to 3, where 0 indicates no pain, and 3 indicates severe pain. Subjects were assessed at the start and the end of the study. The results of both HAQDI tests were exactly the same for each subject and the pain scale ratings were approximately the same between the two tests. The falls risk assessment results are also presented. The falls risk was assessed on an ordinal scale as very low, low, mild, moderate or marked.

8.5.3 Use

Subjects wore the device for a total of 426 days, for an average of 11.15 hours a day (range 1–17 hours). The breakdown of these statistics for each subject are given in table 8.22.

8.5.4 Technical Performance

Overall, the technical performance of the system was good and useable data were collected from all six systems.

Computers

The pentium computers used in the study were adequate for purpose. They had capacity to store four weeks' worth of TA data. No data were lost or corrupted by the machines. Subjects 1 and 2 chose to turn their computers off each night before going to bed and they experienced no technical difficulties with the computers. The remaining four subjects left their computers running continuously. Subjects 3, 4 and 5 each reported a small number of computer crashes (one crash for subject 4, two crashes for subject 3, and three crashes for subject 5), but these were overcome by rebooting the system. This was able to be done by the subjects themselves without the need for investigator intervention. Although all of the machines had the same technical specification, subject 6 experienced more problems with the computer than the other subjects (more than 6 crashes). In most instances the subject was able to rectify the problem by rebooting the system without the need for assistance but in two instances investigator intervention was required.

TA units

The technical performance of the TA units has been reported in the earlier chapters. However, two issues pertaining to their performance became apparent during this study. Firstly, the prototype TA units were insufficiently robust, and secondly, the construction of the TA units was such that it allowed movement of the componentry within the TA units.

Two of the six TA units suffered faults caused by bad solder joints. After one week of use it was observed that the z-axis signal from the TA unit of subject 2 consisted of noise rather than acceleration signal. The subject explained that he had dropped the TA unit and that its performance had been changed since that time. The unit was replaced with a spare unit that was recalibrated. The TA unit of subject 4 failed completely due to a bad solder joint. A week's worth of data was lost before the fault was rectified. No technical problems were encountered with the other four TA units.

Movement of the componentry within the units meant that the d.c. offset calibration of the units changed as the units were worn in. The TA units were tested and calibrated before being installed in the field. They were recalibrated on installation, after 2 weeks and after 4 weeks of operation, and at the end of the study. Significant changes were measured in the d.c. offset of the device between the initial calibration and the 2 week calibration but, after this time, none of the units showed any fluctuation in calibration and no further adjustments to the calibration were made.

These issues indicate that consideration needs to be given to the manufacture of the TA units. Techniques to seal the components in place and to make the unit robust against falls and rough handling need to be investigated. These are discussed in section 9.2.

Wireless Operation

Careful placement of the receiver unit was required to ensure adequate reception about the home. The receiver unit was originally installed in the location that was favoured by the subject. The subject was asked to walk through each room in the home while holding the TA unit. The investigator observed the receiver unit to see whether a signal was being received. If the performance of the system was not satisfactory then the receiver unit was moved to a new location and the process was repeated until a satisfactory location was found. The measure of a satisfactory location was somewhat subjective and did depend on the home in which the installation was taking place. Ideally, the system was satisfactory when the signal could be reliably received from every room. If this was not possible then the best reception that could be achieved was accepted.

In general, the receiver needed to be placed near to the centre of the home. In the testing, the final placement location gave access to almost all of the home (estimated to be around 90%), in five of the six homes. In these, the loss was at the limits of the range; there were not obvious "dead spots" in the home but rather, reception failed at the extremities of the further rooms. The receiver was placed in the living room in three instances, and in a spare bedroom in two instances.

In the sixth case, the subject lived in a large flat located close to a television transmission tower. The subject reported that her home had poor television and radio reception. Her flat included a rooftop garden. The TA unit had reception over somewhat less than half her home, and no reception in the rooftop garden. There were dead spots about this home. The flat was built as a large open plan living area with the kitchen in the centre. The bedrooms were built as wings off this central area. The receiver unit was located in the main bedroom from where it received TA signals from the nearer living area, part of the kitchen, and the further living area that was not directly behind the kitchen. There was no reception from the further half of the living area, nor the other bedrooms.

For clinically critical monitoring or for a personal alarm system, better reception is needed. There are several possible means for achieving this and these are discussed in section 9.2.

Battery Performance

Grandcell AA 1.5 V rechargeable batteries were used for the study. In tests, a new battery lasted for around 80 hours of continuous transmission and could easily last for a twelve hour day of transmission before being recharged. Grandcell state that these batteries are good for 25 or more recharges [17]. In fact, the Grandcell website stated that "if used correctly, Grandcell can provide well over 100 recharges during its service life" [17]. However, after around 15 recharges, the battery only lasted for half a day before needing to be replaced. Subjects were provided with a set of four batteries, and subject 1 who used the system for the longest time was provided with a new set of batteries during the study. Subject 2 stated that he changed the battery twice a day during the last month of the study because he noticed that as the battery discharged the transmission range was reduced.

Based on these results, and with the same level of power consumption, a new set of four batteries is required every two months, which amounts to 24 of these batteries per year.

8.5.5 Data Analysis

A Case Study Example

Subject 1 kept notes of her daily activities during the study period. The results of the processing were compared to these notes. Good agreement was found between the two. In this section, a subset of the data obtained during the course of one day is presented, together with the notes provided by the subject. The intent of this is to illustrate the relationship between the movements described in the subject's notes and the acceleration signals that were obtained.

Data taken from subject 1 on 9th September 2002 are presented as typical examples of the data obtained from the subjects. The notes made by the subject on this data are given in figure 8.11. A detail of the TA signals recorded on that day between 11:48 a.m. and 1:12 p.m. are shown in figure 8.12. It can be seen by looking at the signal that the subject moved around until just after noon, when she sat down—for lunch, according to her notes. Half an hour later she got up and moved around—while cleaning up after lunch. Then she sat down again—in order to write a letter, and the TA slipped off her skirt. This event is visible in the signal trace as the large spike on all four axes just after 12.8 hours. The subject then remained sitting for the rest of the time shown in the graph.

The proportion of transmitted data that were captured, the proportion of time

9^{th} Sept:	
7.25 :	*Set machine. Everything seems to be working properly.* *Breakfast & then domestic chores until 10.45 am.* *Rested until 11.30 am.*
12 noon:	*Lunch time, clear up etc.*
12.50:	*Sat down to write a letter - monitor slid off my skirt, caught it before it reached my knees.*
1.47 pm:	*Had to race off as I had dental appt for 2 pm.* *Haven't walked so fast, so far in a long while. And then found Dentist had gone on vacation!! Bought fruit etc.* *I had to sit & rest on bus seat on way home.*
3.15 pm:	*Home, - made some tea, sat & read newspaper for quite some time.*
8.00 pm:	*Changed into dressing gown.*
9.30 pm:	*Shut down.*

Figure 8.11: Example of the notes made by subject 1 regarding her daily activities during the study period.

for which the subject wore the device, the proportion of time that the subject spent engaged in activity, and the mean SMA per second were each computed for each hour.

Figure 8.13 shows the percentage of transmitted data that was captured by the receiver unit on an hourly basis. At 1:47 p.m. the subject left the house and did not return until 3:15 p.m. No data were captured during this period so it can be inferred that the subject wore the TA unit while she was out. The subject was in her home for most of the remainder of the day but the signal from the TA unit was not always received.

Figure 8.13 also shows the proportion of time for which the subject was determined to be wearing the TA unit. The subject was determined to be wearing the TA unit all of the time that data were captured, except for the last hour, between 9 and 10 o'clock at night, when the subject was deemed to have worn the unit for 60% of the time. The subject recorded that she shut down the system at 9:30 p.m. According to the log file, logging ceased at 9:36 p.m. The system identified that the subject was not wearing the device from 9:10–9:24 p.m. Inspection of the signal revealed that the acceleration vector was not changing during this period. Following this there was a short burst of vigorous movement and then the logging stopped.

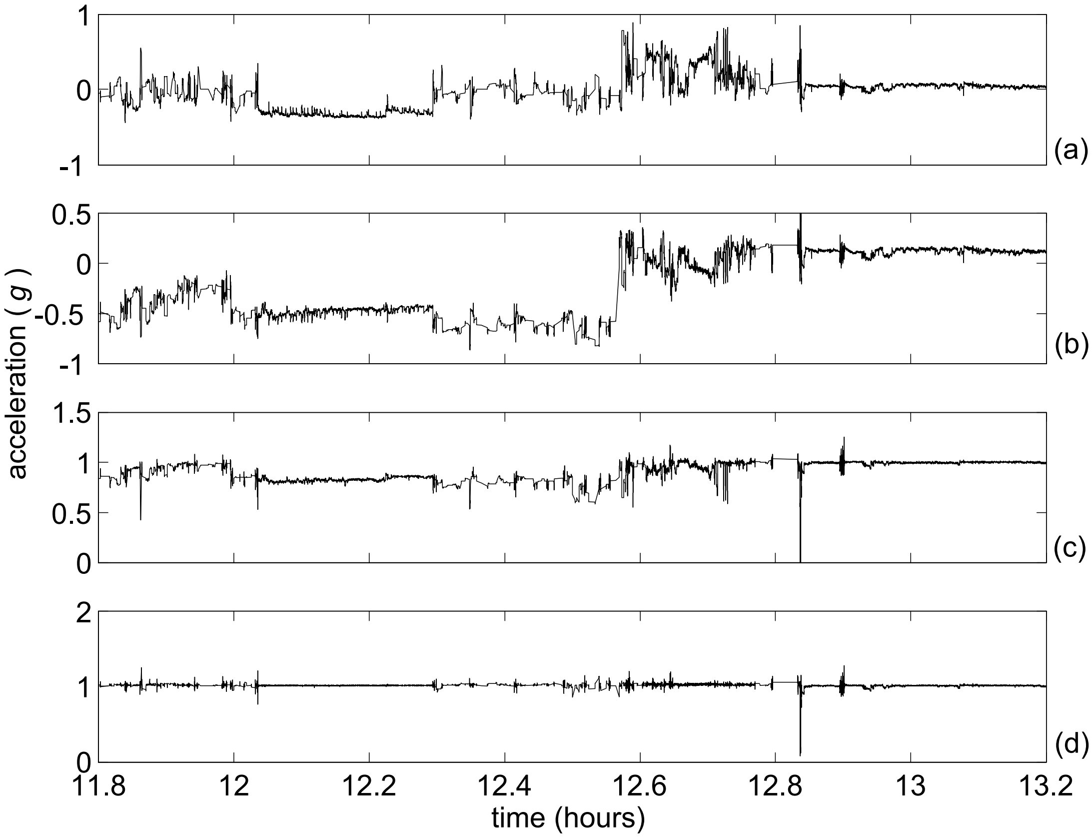


Figure 8.12: TA signal from subject 1 between 12 and 1 o'clock on 9th September. (a) x-axis, (b) y-axis, (c) z-axis, (d) acceleration magnitude, ρ. Note the different acceleration ranges on the vertical axes. Just after noon the subject sat down for lunch. Half an hour later she got up and moved around while cleaning up after lunch. Then she sat down again and the TA unit slipped off her skirt (this is indicated by the large spike on all four axes just after 12.8 hours). The subject then remained sitting for the rest of the visible trace.

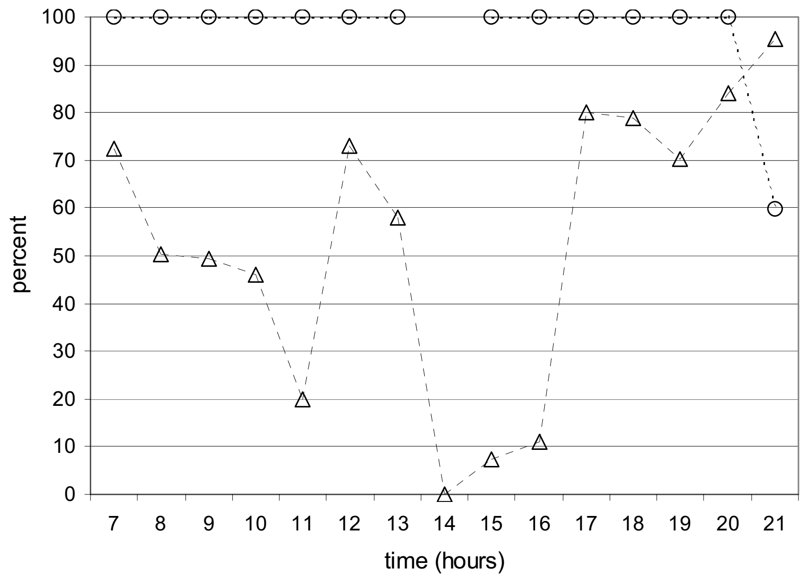


Figure 8.13: Monitoring results for subject 1 on 9th Sept. Δ: Percentage of transmitted data that was captured, and O: Percentage of time for which data were captured and subject was wearing the TA device.

This signal trace is consistent with the subject deciding to go to bed, taking off the TA unit and placing it on the table while she prepared to go to bed, then picking up the TA unit and removing the battery for recharging, before turning off the computer.

Figure 8.14 shows the hourly mean normalised SMA values for the day. The hourly mean SMAs that were generated while the subject was engaged in activity and in rest are also shown in the figure. It can be seen that when the subject was engaged in activity, she was most vigorous from 12–1 p.m., and from 4–5 p.m. The 12–1 p.m. activity was the preparation for, and cleaning up after, lunch. The 4–5 p.m. activity was not described by the subject. Both of these periods of activity took place after an extended period of rest, according to the subject's notes. Her mean levels of activity were higher during these times than during the earlier hours of the day when she was engaged in sustained housework activity. It is to be expected that the subject would be more vigorous during relatively short periods of activity following periods of rest, than during extended periods of work.

Figure 8.15 shows the proportion of time that the subject spent engaged in activity. The subject spent the most time engaged in activity from 11–12 noon and from 3–4 p.m. These two hours also recorded the highest mean SMA overall

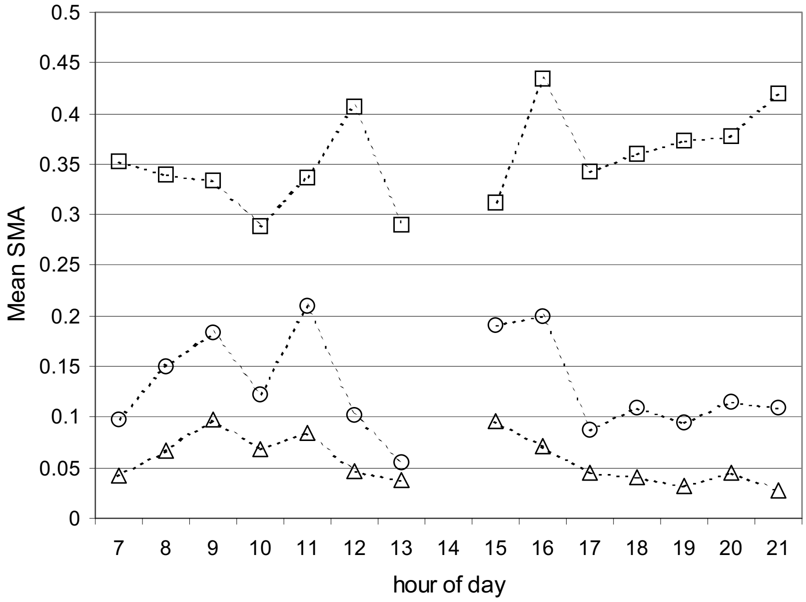


Figure 8.14: Hourly mean recorded signal magnitude area (SMA) for subject 1 on 9th Sept. O: Overall hourly mean SMA, □: hourly mean SMA for periods of activity, and Δ: hourly mean SMA for periods of rest.

(figure 8.14). However, there was not a direct correlation between the overall SMA and the amount of recorded time spent engaged in activity. This is illustrated in a comparison of the subject's activity from 9–10 a.m. and 10–11 a.m. From 9–10 a.m. the subject spent 45% of her time in activity, as compared to 58% the following hour. However, the overall mean SMA was greater for the hour from 9–10 than for the following hour because the subject's movements became less vigorous in the second hour.

All of the other data recorded by this subject were compared to the description of activities provided by the subject and the agreement between the two was good in every case. After several weeks the subject began taking off the TA unit and leaving it beside the receiver unit whenever she went out.

The same parameters were computed and tracked on an hourly basis for every day that the subject wore the TA unit. They were also tracked on a daily basis. The same procedure was applied to the data from the other five subjects except that no record of activities had been kept and so no activity verification was undertaken.

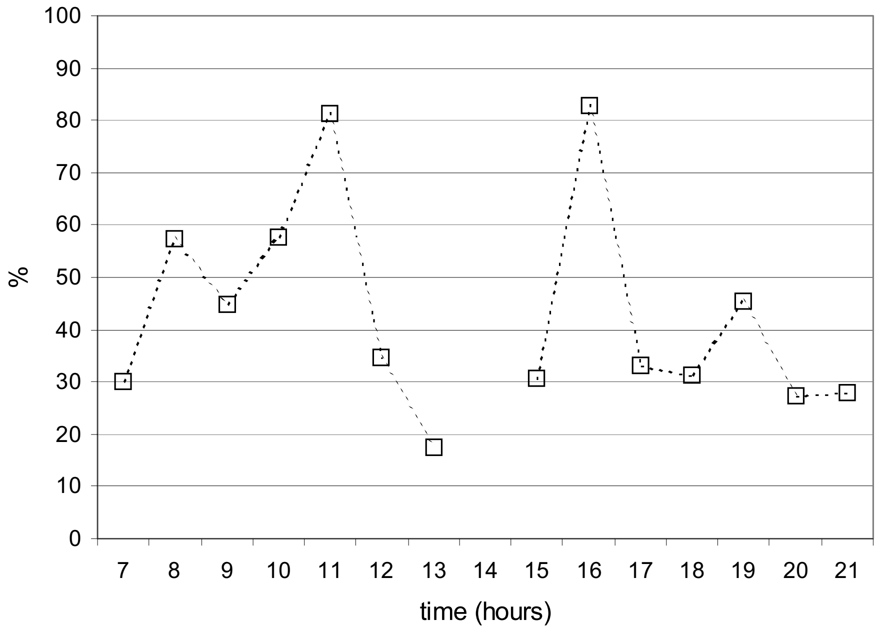


Figure 8.15: Monitoring results for subject 1 on 9th Sept. □: Percentage of time for which subject was recorded as wearing the TA device and engaged in activity.

Data Capture Rates

Overall, 63.5% of the transmitted data were received. The average data capture rates for each of the six subjects are given in table 8.23. Data were lost when the TA unit was out of range of the receiver. This could occur if the subject left home while wearing the TA unit, or if there was insufficient reception in some areas of the home. In general, there was no way of distinguishing between times when a subject went out wearing the TA unit, and occasions when the subject was at home and data were not received.

Subject 2 recorded the least amount of data captured. This subject also reported that he spent most of each day away from home and that he often wore the TA while he was out.

Falls Detection

No falls or stumbles were reported by any of the subjects during the course of the study. Large acceleration magnitudes (exceeding 1.8 g for at least 3 consecutive samples) were detected on sixteen occasions but none of these were indicative of a fall. In each case, the device was either not being worn or the subject remained in an

Subject	% data captured
1	71.04
2	33.61
3	71.23
4	45.19
5	67.58
6	89.41

Table 8.23: Data capture rates for study 4F.

upright posture after the event, and continued performing activities either immediately after or shortly (several seconds) after the event. The events are summarised in table 8.24.

In seven of the cases, the event was not caused by body movement. On three occasions the subject was putting on, or taking off the TA unit. On four further occasions the TA unit was not being worn, but was picked up and shaken then replaced. These four events all occurred during investigator visits and were caused by the investigator who was demonstrating the functionality of the system to the subject.

Statistical Analysis

The data were tested for hourly and daily trends in amount of data captured, percentage of time that the unit was worn, amount of time spent in activity and mean SMA. The data were also tested for correlations between self-reported health status, time spent in activity and mean SMA. All tests were carried out using the complete data set from all six subjects.

A strong correlation was found between mean hourly SMA and proportion of time spent in activity each hour (Spearman-rank $r = 0.951$). A scatterplot of the data is presented in figure 8.16. A moderate correlation was detected between coop/wonca health score and mean SMA ($r = -0.507$). A scatterplot of the data is presented in figure 8.17. A weak correlation was detected between Coop score and the amount of time spent in activity over the course of a day ($r = 0.157$), but it was not statistically significant ($p = 0.069$). No correlations were found between any of the measured parameters and time (either hour of day or day of study).

Subject	Before	After	Possible Cause
1	upright, general movement	upright, general movement	unit fell off skirt (this was recorded by the subject)
1	upright, general movement	upright, general movement	unit fell off skirt
2	lying face down, unit not worn	lying face down, unit not worn	unit picked up and shaken
2	upright, general movement	upright, resting	
2	upright, general movement	lying face up, unit not worn	unit taken off
2	upright, unit not worn	upright, unit not worn	unit picked up and shaken
2	upright, general movement	upright, general movement	
2	upside down, not worn	upright, general movement	unit put on
3	upright, general movement	upright, general movement	unit picked up and shaken
4	unit not worn, then general mvt	upright, general movement	unit put on
4	upright, general movement	upright, general movement	
5	upright, vigorous movement	unit rested on each face in turn, unit not worn	unit picked up and shaken
5	walking	walking	subject may have stumbled and not recorded the event, or device may have been knocked
6	lying right side, resting	lying face down, resting	lying-to-lying transition
6	vigorous movement	vigorous movement	these two events occurred within a period of 2 minutes. The subject was engaged in vigorous cyclical activity. The signal patterns were similar to those generated during walking, but the accelerations generated were twice those generated by a subject walking rapidly (120 steps / min). The signal exceeded the 1.8g threshold most periods of the movement It may have been generated by stamping or running. The activity occurred at 7 o'clock at night.
6	vigorous movement	vigorous movement	see above

Table 8.24: Summary of large acceleration magnitudes generated in study 4F.

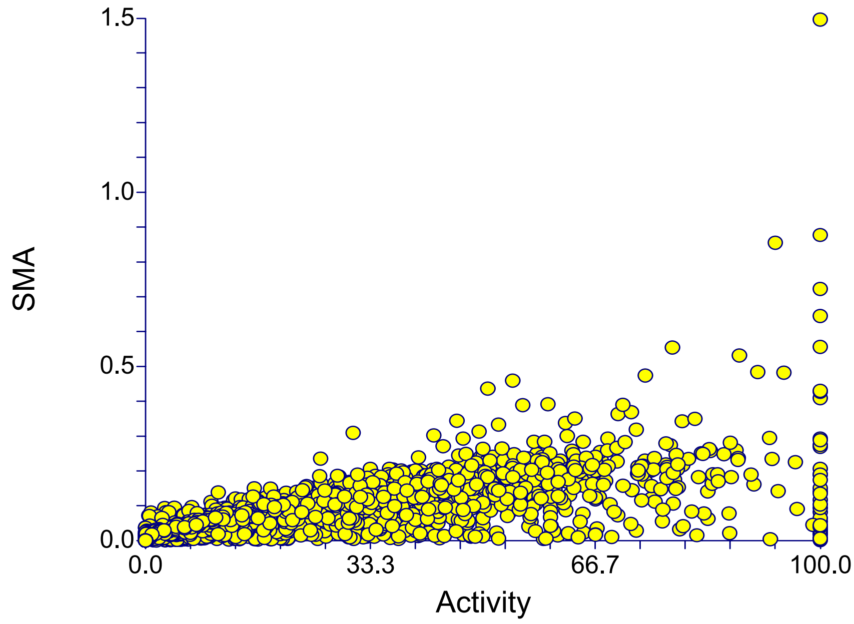


Figure 8.16: Scatterplot showing mean hourly SMA plotted against mean hourly percentage of time spent in activity across all subjects in study 4D ($N = 6$).

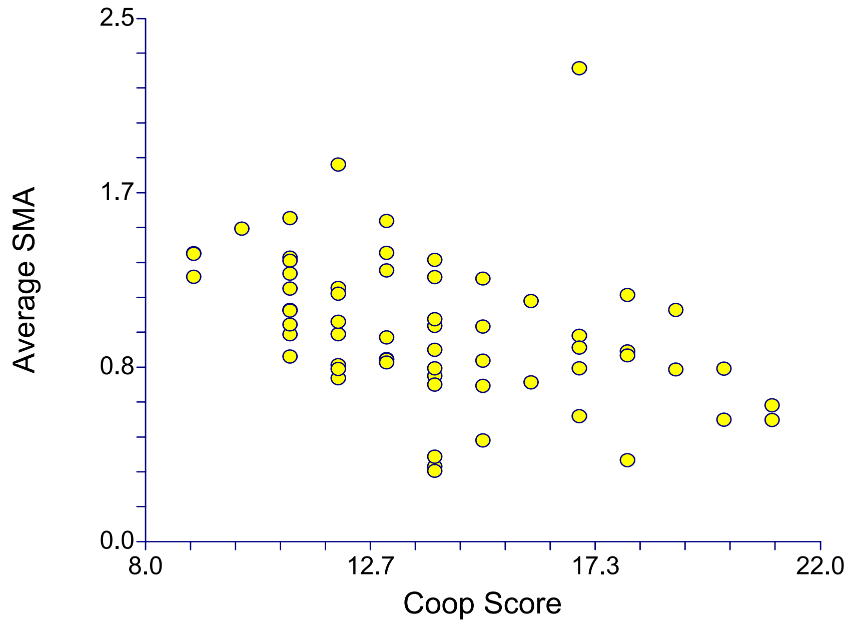


Figure 8.17: Scatterplot showing mean weekly SMA plotted against coop/wonca score across all subjects in study 4D ($N = 6$).

8.5.6 Discussion

This pilot trial evaluated the use of the TA unit for unsupervised, long term monitoring of human movement. Although several issues pertaining to the technical performance and the useability of the system were raised, all of the subjects were able to use the system without difficulty after a short period of use. None of the subjects found wearing the unit inconvenient, nor did they find performing the daily routine inconvenient. The subjects who wore the unit for extended periods commented that they often forgot that they were wearing it. Subjects were happy with the size and the shape of the unit.

Although the basic system was well accepted the study also revealed several shortcomings that should be rectified. In particular the TA unit push button, attachment clip, and power supply should be redesigned and the TA unit transmission power should be boosted.

All subjects showed a high rate of compliance in using the system and in performing the directed routine. The system generated an audible reminder if the subject had not completed the routine by a specified time. Subjects were also contacted on a weekly basis by the investigator. These measures may have helped to maintain high compliance rates.

Several of the elderly subjects reported that they needed to move the attachment position of the device because of rubbing at the attachment site. Thus it is important that the interpretation system is able to interpret data obtained from different locations on the waist. As discussed in the earlier chapters (5 and 6), it was able to do so provided that the placement location was known, and the placement location was able to be identified from the average acceleration vectors obtained from quiet standing and supine lying during the daily routine. Signals from the daily routine were also able to be used to determine baseline values for standing and sitting tilt angles and SMA, which could be used in the activity identification algorithms for the identification of activities during free movement, if required.

The best time for the directed routine to be carried out is first thing in the morning so that the day's positioning information is available for the monitoring of free movement from the earliest possible occasion. This was also the time that was preferred by all of the subjects.

Introduction of the directed routine into the daily programme had a number of benefits:

- it reduced the amount of data processing that was required;
- it ensured that each important movement was performed in the same manner each day so that parameters could be longitudinally tracked and compared; and
- it ensured that movements from which parameters were extracted were classified with a very high level of accuracy.

The free movement was processed on a second-by-second basis. The 1 s window was chosen because this provided close to optimal results for the activity detection algorithm and it also meant that fall events could be detected promptly. Each second the additional SMA was computed and added to a running total. The total and mean for each hour was stored, and at the end of the day, the daily mean was computed. This process required only one buffer 45 samples long (at a sampling rate of 45 samples per second) and a second buffer 60 samples long (one sample per second) to determine whether or not the subject was wearing the TA unit. It was sufficiently efficient to be carried out in real time, as the data were received, on a regular personal computer. It could potentially also be carried out on the TA unit itself if appropriate enhancements were made to the technology.

Although none of the subjects suffered any significant accidents or illness during the study period and no longitudinal trends were detected in the data from the directed routine, the subjects' health did fluctuate slightly during the study period. This was captured in the coop/wonca health scores. The coop/wonca charts are well validated and reliably reflect the overall self-perceived health status of the subject [224]. The moderate negative correlation obtained between the coop/wonca scores and the mean weekly SMA indicates that when subjects felt less healthy they engaged in less physical activity. Further studies using statistically large samples of subjects are needed, but this preliminary result lends support to the hypothesis that the TA unit can be used for preventative health monitoring by detecting early changes in overall health status through changes in mean SMA. Future work should also involve field trials to capture data from subjects with poor health, whose health is likely to change significantly during the study period, and from subjects who have a high risk of falling so that relationships between health status, fall events and parameters from the TA signal can be investigated.

8.5.7 Conclusion

In long-term, unsupervised use, subjects chose to wear the TA unit at different positions on the waist, and even to wear the unit at different positions on different days. It is thus important to be able to analyse the signal regardless of the placement. As discussed in chapter 6, all of the algorithms that were used to identify movements and to extract parameters could be applied to any placement on the waist, provided that the placement was known. The placement could be determined from the directed routine, by analysing the acceleration vectors generated during quiet standing and supine lying. The directed routine also provided baseline data on standing and sitting tilt angles and mean SMA values for the activity classification algorithm.

In the instances where a log of movements was kept by the subject during free movement at home, the accelerometer signals showed good agreement with the log.

Parameters of energy expenditure (SMA) and the proportion of time spent in activity were computed on an hourly and a daily basis. There was a strong correlation between these two parameters ($r = 0.951$) when compared on an hourly basis.

A moderate negative correlation was obtained between weekly self-perceived health status (coop/wonca score) and mean energy expenditure (SMA) of $r = -0.507$. This preliminary result lends support to the hypothesis that the TA unit can be used for preventative health monitoring by detecting changes in overall health status through changes in mean SMA.

8.6 Chapter Conclusion

The results of four experimental studies were presented in this chapter. The studies encompassed the use of the TA unit for monitoring directed and free movements in laboratory and home environments, and under supervised and unsupervised conditions.

The purposes of the directed routine were

- to provide daily baseline data for the subject, including tilt angle and SMA when sitting and standing; and
- to collect parameters of movement that could be tracked longitudinally.

The movements in the directed routine were automatically identified using a combination of button presses, the activity classification algorithm presented in section 6.11, and heuristic rules. This identified the activities and movements with at least 97.8% accuracy.

Overall, the results obtained in the three studies of directed movement showed a high degree of consistency. There were no significant differences in the sets of parameters obtained in the supervised laboratory study, the unsupervised laboratory study, and the supervised home study. Parameter values were similar for all subjects, and were also consistent within individual subjects. Moreover, all subjects found the system easy to use, and all reported that the TA unit was comfortable and convenient to wear. These results indicate that the waist mounted TA is a reliable instrument for monitoring movement in an unsupervised home environment.

In every subject cohort, there were statistically significant differences between the acceleration vectors obtained during quiet standing, sitting and lying. There were several statistically significant differences between the parameters obtained from the elderly cohort and those obtained from the younger cohorts. The elderly group recorded lower SMA values and smaller acceleration ranges for all activities but the stand-to-sit transition. They also recorded greater SMA values and acceleration ranges during the 30 s stand and during the lying period. From these results it can be concluded that the younger cohort were able to remain more still than the older cohort during rest periods, and moved more vigorously during periods of activity than the elderly subjects. The elderly subjects took slightly longer to complete the sit-to-stand transition (3.5 ± 1.3 s, as compared to 2.6 ± 0.8 s). There was no difference in the amounts of postural sway between the groups, nor were there any differences in gait cadence or variability.

No fall events occurred during any of the studies. During study 4F, sixteen abnormal acceleration events were identified, but none of these were followed by a lying posture. Seven of these incidents were not related to body movements, occurring when the subject took off, or put on the TA unit, or when the TA unit was picked up and shaken (caused by system demonstration during an investigator visit).

In long-term, unsupervised use, subjects chose to wear the TA unit at different positions on the waist, and even to wear the unit at different positions on different days. It is thus important to be able to analyse the signal regardless of the placement. As discussed in chapter 6, all of the algorithms that were used to identify movements and to extract parameters could be applied to any placement on the waist, provided that the placement was known. The placement could be determined from the directed routine, by analysing the acceleration vectors generated during quiet standing and supine lying. The directed routine also provided baseline data on standing and sitting tilt angles and mean SMA values for the activity classification algorithm.

In the instances where a log of movements was kept by the subject during free movement at home, the accelerometer signals showed good agreement with the log.

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A moderate negative correlation was obtained between weekly self-perceived health status (coop/wonca score) and mean energy expenditure (SMA) of $r = -0.507$. This preliminary result lends support to the hypothesis that the TA unit can be used for preventative health monitoring by detecting early changes in overall health status through changes in mean SMA.

Chapter 9

Future Directions

9.1 Overview

The current work has demonstrated the feasibility of using accelerometry for unsupervised home monitoring. It has rigorously analysed the signals obtained from a TA, and developed an understanding of the component signals and the way in which they can be used. It has developed a system for using a single waist mounted TA unit to monitor human movement in an unsupervised home environment. A framework for signal identification and classification has been introduced. Algorithms for discriminating between periods of activity and periods of rest, and for identifying and classifying movements have been developed and evaluated. It has been demonstrated that once movements have been identified, clinically sensitive parameters can be extracted from the signal. A two stage monitoring process has been introduced in order to allow longitudinal tracking of sensitive parameters and monitoring for adverse events. This process has been assessed in a pilot study with six elderly subjects over a three month period.

Additionally, in the course of the current work a number of issues worthy of further research and development were raised. This chapter discusses the recommendations for future work that have arisen as a result of the current work.

9.2 Technical Enhancements

Improvements to the TA Unit

During the course of testing undertaken in the current work it became apparent that some aspects of the TA unit needed to be improved. These were the robustness of the unit, the choice of power supply, the design of the push button and the design of the attachment clip. These are discussed in the following sections.

The TA unit needs to be more robust. Two problems arose during testing because the TA units were not sufficiently robust. Firstly, the componentry within the TA units shifted during initial use. Secondly, two of the units failed during the pilot field study due to bad solder joints. The units were not specifically manufactured to tolerate being knocked and dropped. These problems could be prevented through the use of different manufacturing techniques. For example, the unit could be filled with resin to set the components in place. It is important that the components cannot shift during use so that the unit does not go out of calibration or fail if it is dropped or knocked.

An improved power supply is required. The TA units used in the current work were powered by a single AA battery. An alkaline battery provided around 80 hours of continuous transmission before needing to be replaced. In the pilot study, rechargeable AA batteries were used and recharged every night. After several weeks of practice, none of the elderly subjects in the pilot trial found this a difficulty or an inconvenience. However, the subject must remember to change the battery. Additionally, manipulation of the batteries requires finger strength and coordination and may be too difficult for frail elderly or ill subjects. Consequently, consideration should be given to alternative approaches to powering the TA unit.

One possibility is to use a battery that can be recharged by means of an inductive coupling. The a recharger cradle could be designed for the TA unit, similar to those used for mobile telephone batteries. Each evening, the subject could place the entire TA unit in the recharger. This would alleviate the need for changing the battery each evening. It also means that the unit remains active during the night, should the subject need to press the personal alarm button.

Battery life in the TA unit was short because the data were transmitted continuously. If the amount of data transmission was reduced, this would increase the life of the battery.

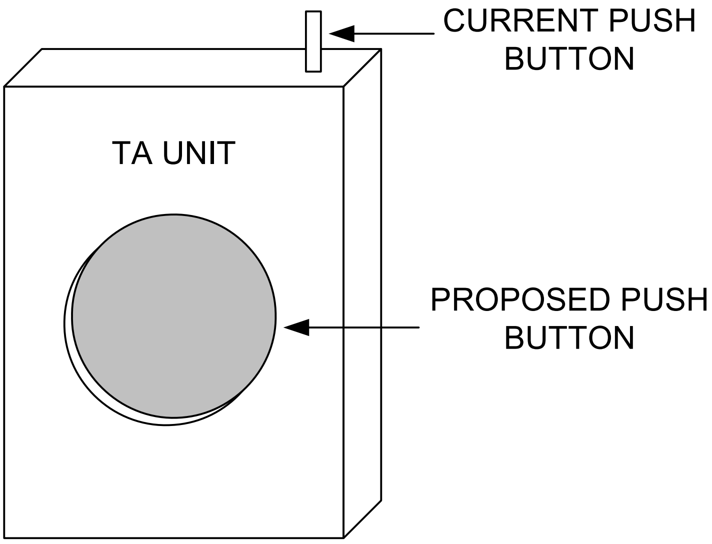

Figure 9.1: Illustration of the TA unit showing the current and proposed push buttons.

The push button needs to be redesigned. In the prototype design, the push-button was a small protruding knob attached to the top face of the TA unit. The small size of the button made it difficult for subjects to find. Its small surface area led to concerns about it piercing the skin. Its position on the top face made it difficult for some subjects to reach when the TA was worn at the waist as it became buried under soft tissue. Replacing the existing button with a large recessed button on the front face of the device would solve these difficulties (see figure 9.1).

The attachment clip needs to be redesigned. Two elderly subjects found that the clip on the TA unit did not grasp firmly enough and the unit slipped off when bending over or toileting. A new clip is required that grasps more firmly, without damaging the fabric of the clothing.

Increasing the Data Capture Rate

During testing the TA system was found to have a line-of-sight transmission range of 50 m. It was also found to function reliably throughout the three houses in which it was tested (refer to section 4.4). However, data were lost during periods of monitoring subjects at home in the studies of free movement (refer to sections 7.7, 7.8, 8.4 and 8.5). The range over which data were received also decreased as the battery discharged. It is important that the system function reliably throughout the home if it is to offer capabilities as a personal alarm system.

Three approaches that could be investigated for improving the data reception rate are:

1. increasing the TA unit transmission power,

2. installing repeater units around the home, and

3. changing to a wireless transmission frequency that is less susceptible to interference.

Improvements to the Receiver Unit

The elderly subjects who participated in the pilot study responded negatively to the introduction of a personal computer into their homes. Consideration should be given to redesigning the TA system in such a way that the personal computer is not required. The functions of the personal computer were data processing and storage, and the provision of a user interface for the subjects. These functions could be added to the receiver unit, so that the personal computer and monitor are no longer required.

Data Processing Location

In the current work, all data captured by the TA unit were transmitted to the receiver unit and stored by the personal computer. This was essential in order that the signals could be studied and algorithms developed. However, the high rates of transmission reduce the life of the battery in the TA. If some data processing was undertaken in the TA unit then less data would need to be transmitted and hence less battery power would be consumed.

There are three basic models for data processing:

1. All of the data are transmitted from the TA unit to the receiver unit and the data processing is carried out at the receiver end. This was the method that was used in the current work.

2. All of the processing is done in the TA unit and only relevant parameters are transmitted. This requires the least amount of data transmission. The drawback is that as the raw data is not stored, it cannot be reviewed should further information be required.

3. The TA unit makes some decisions about which data to transmit but the bulk of the processing takes place at the receiver end. For example, the TA unit

might only transmit data when the conditions for a fall event have been met, and it would then transmit the raw acceleration data.

The recommended approach is a combination of the three methods. It is proposed that the TA unit has two modes, one in which all of the data are transmitted, and one in which only important parameters are transmitted. During the directed routine, all of the data are transmitted and are processed at the receiver end. This ensures that the original data are available for all of the important movements that are tracked longitudinally. During periods of free movement, data processing is carried out in the TA unit. Parameters of time spent in activity and SMA are computed and transmitted on an hourly basis. These data are then stored at the receiver end. Carrying out this processing in the TA unit has the added advantage that no data are lost in transmission before the computations are made. During periods of free movement the TA unit also monitors for large accelerations, which may be indicative of fall events. If a large acceleration peak is detected, then the TA unit switches modes to transmit all of the raw data to the receiver unit. If the subject did not fall, or falls and rises again, the TA unit switches back to the onboard processing mode after the subject has recovered. If the subject did fall and did not rise again, then the TA unit continues to transmit all of the data until it is reset.

The hourly reporting during free movement also provides an indication that the TA unit is functioning properly. Handshaking between the TA unit and the receiver unit could be introduced so that if an hourly report is not correctly received, it is re-sent, with the request being maintained by the receiver unit until the data are received. Then, if the TA unit is out of range of the receiver, the parameters can be stored until the unit comes back into range when they can be transmitted. If the receiver unit does not receive an hourly data set for a period of time that exceeds a preset threshold then an alert can be generated to indicate that the TA unit may be faulty.

This method would require the TA unit to be redesigned with more data processing and storage capability, but would be expected to reduce the load on the battery, and the requirement for data storage space at the receiver end would also be greatly reduced as only small amounts of raw data would need to be stored.

9.3 Physiological Understanding of the Signal

Modelling of Pelvic Acceleration During Gait

In the current work it was found that a simple model of the surface area of the subject at the waist could be used to relate TA output, device placement and postural orientation during periods of rest. The same model could be used to relate the signals obtained from different placements at the waist during sit-stand-sit movements. However, this model could not be used to relate the acceleration signals obtained from different placements at the waist during walking, and neither could a simple biomechanical displacement model.

The relationship between the signals from a waist mounted TA and parameters within the gait cycle is not well understood. Further work should involve studying the ways in which parameters of gait such as single and double stance times are characterised within the acceleration signals at different places on the waist.

It would be useful to develop an acceleration-based model that relates acceleration signals obtained during gait from different parts of the waist. This would then allow the direct comparison of parameters within the gait cycle from acceleration signals taken at different places on the waist, which would in turn allow these parameters to be monitored in an unsupervised setting.

Modelling the Relationship Between SMA and EE

There has been shown to be a high overall correlation between SMA (signal magnitude area) and EE (metabolic energy expenditure) during routine daily activities [31]. However, the optimal regression parameters change with different activities and in some circumstances the general regression equation does not result in a good estimate of EE [34, 74, 98, 210]. Future work should involve developing a better understanding of the relationship between SMA and EE for different activities. The activity classification framework could be used to identify the activity and then the EE could be computed from the SMA using the optimal regression parameters for that activity to provide more accurate estimates of EE during daily living.

9.4 Enhancement of the Classifier Framework

Functionality for Self-Correcting Classifications

The activity classification framework that was developed and described in the current work consisted of a binary tree with "ripple down" rules. The introduction of backpropagation to this framework should be considered. If a decision is made and the process ripples down to a lower level of detail, where it is found that none of the sub-classifications adequately describe the actual movement, then the possibility that the original classification was incorrect should be considered. In this case, the process should return to the higher level of detail, reject the classification that was previously made, and continue along the processing flowchart in search of another movement that matches the actual movement. This type of approach could allow the system to become self-correcting.

Functionality for Adaptive Learning

Each time that the system is used and a classification is made, parameters of the movement could be recorded and, over time, a subject-specific template could be developed for each movement. Pattern-matching techniques using these templates could then be employed to support classification decisions.

Development of a Heuristic Overlay

In study 3F (refer to sections 7.7 and 8.4) a set of rules was developed to assist in classification of free movement. After the classification algorithm had been applied to the acceleration signals, the rule-based system examined the sequence of classifications. If an impossible sequence of classified movements was identified then the rules were used to correct the classifications. This system provided improved classification results for the two data sets on which it was tested. It also ensured that the classification decisions resulted in a reasonable sequence of movements. Future work should further investigate the use of a heuristic overlay to check and correct the decisions made by the classification algorithm.

9.5 Algorithmic Development

Identifying When the Device is Not Being Worn

If the recorded level of movement is below the threshold at which it is certain that the TA unit is being worn, then there is no way of telling, based on the root mean square acceleration value alone, whether the subject is wearing the TA unit and lying very still, or whether the TA unit is not being worn (refer to section 6.4). Heuristic methods may be able to make this decision by considering the movement leading up to the period without motion.

However, a simpler and more reliable method is to introduce a recharger cradle into the system, such as was described in section 9.2. A protocol could be established in which, whenever the subject is not wearing the TA unit, it is placed in the recharger cradle. The recharger cradle could acknowledge receipt of the TA unit, and then it would be certain that the TA unit was not being worn. Then, it could be assumed that the TA unit was being worn whenever it was not stored in its cradle. If the recorded r.m.s. value was below the threshold for an extended period of time then this may indicate that the person is unable to move, or is unconscious, and help is required, and the system should raise an alarm. If the alarm is false (because the person was not wearing the TA unit and did not comply with the procedure) then the person can cancel the alarm (refer to section 9.8).

Discriminating Between Sitting and Standing

The sit/stand posture classifier algorithm introduced in the current work (refer to section 6.6.5) used decoupled inputs. Future work could involve investigating the performance of an algorithm with input coupling.

Assessing Postural Sway

Preliminary work has indicated that the accelerometer is capable of identifying parameters relating to postural sway. Future work in this area should involve laboratory-based validation tests with statistically significant sample sizes. The output of the TA also needs to be understood in clinical terms as well as being correlated to other measurement techniques. If this is achieved then the TA can be used as a tool for the investigation of postural sway under free living conditions in the target subject group. A methodology for the evaluation of the accelerometer an instrument for the measurement of sway is described.

Proposed Experimental Methodology

A representative sample of at least 200 subjects should be recruited. Subjects should be drawn from the population of elderly (aged 65 years and over) community dwellers. Each subject should be asked to perform four tests:

1. Stand on firm surface with eyes open for 30 s,
2. Stand on firm surface with eyes closed for 30 s,
3. Stand on compliant surface (foam block) with eyes open for 30 s, and
4. Stand on compliant surface (foam block) with eyes closed for 30 s.

A force plate should be placed underneath the surfaces on which the subject stands. A swaymeter (described in section 2.4.2) should be attached to the subject to trace the sway path. A TA should be attached to the waist of the subject above the right anterior superior iliac spine.

The TA signals should be compared to the sway path measured by the force plate using the methodology described by Mayagoita *et al.* [163]. The TA signals should also be compared to the values determined by a swaymeter. The Pearson correlation coefficients between the measurements from the three instruments should be computed. Linear regression should be applied to quantify the relationships.

Identifying Falls

The falls detection algorithm was developed and tested using "simulated" falls performed in the laboratory. A data set of genuine fall events from free living subjects needs to be collected, and the performance of the falls detection algorithm evaluated using these events.

Identifying Stumbles

The occurrence of stumbles is one of the predictors of falls. It is hypothesized that stumbles can be identified by abnormally large accelerations, in the same way as fall events, or by unexpected anomalies in cyclic motion. Figure 9.2 shows the acceleration signals generated by a "simulated" stumble during walking. Figure 9.3 shows the acceleration signals generated by a second "simulated" stumble in which the subject fell back into the chair after attempting to rise. In both of these instances the stumble is characterised by a large acceleration spike and, in the first instance, the walking pattern is interrupted at the time of the stumble.

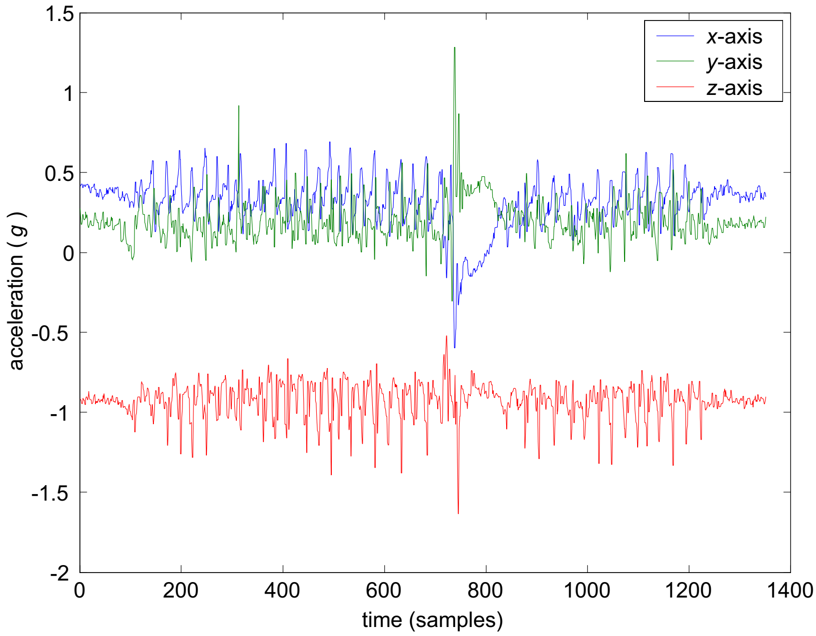

Figure 9.2: Acceleration signals generated by a "simulated" stumble during walking. At the time of the stumble there is a large acceleration spike and the cyclic walking pattern is interrupted.

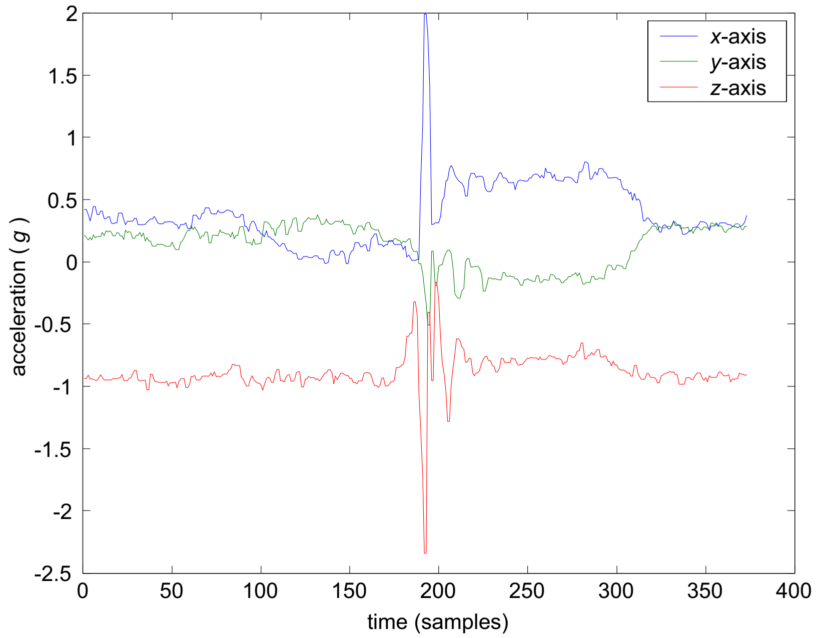

Figure 9.3: Acceleration signals generated by a "simulated" stumble in which the subject fell back into the chair after attempting to rise.

The problem with deliberate stumbles is that they may not reflect the patterns that occur in genuine stumbles because, in the deliberate stumble, the subject does not lose balance control, which is not the case in the genuine event. The subjects who performed the deliberate stumbles were young, healthy subjects, whereas the primary subjects of concern with regard to falls are the frail elderly. The stumbles performed by the young, healthy subjects may have been performed more vigorously, and hence have more clearly defined acceleration patterns, than those that occur in the frail elderly. A set of genuine stumble, and near fall events needs to be collected, and the performance of the abnormal acceleration detection algorithm evaluated in this context.

Identifying Walking with Pathological Gait

The template matching algorithm for the step by step determination of gait period (refer to section 6.8.3) should be evaluated on pathological gaits and on gaits with a high variability.

Discriminating Between Sit-to-Stand and Stand-to-Sit Transitions

In the current work, sit-to-stand and stand-to-sit transitions were most successfully identified and distinguished using an expert system (refer to section 6.9.4). Neural network methods were tested, but they were trained with a data set taken from a single subject, and their classification rates were poor when presented with data from other subjects. However, the comparative success of the expert system indicates that there are parameters contained within the signal that allow discrimination to be achieved and, given a sufficiently large and varied training set, the neural network performance should be able to be improved.

Future work should involve the collection of data from a cohort of free-living subjects at home. These data should be used to train a neural network in order to evaluate its performance when trained with data from multiple subjects, and to evaluate its performance in identifying transitions in the same subject over time.

Accurate Determination of Activity Endpoints - A Preliminary Study

In the current work, endpoints were approximated by the activity detection algorithm. The accuracy of the endpoint detection in this algorithm is dependent on the choice of window width, w.

Preliminary work was undertaken to develop a method for identifying the activity endpoints more accurately. This work is summarised here.

Introduction In the current work, endpoints were approximated by the activity detection algorithm. The accuracy of the endpoint detection in this algorithm is dependent on the choice of window width, w. For most purposes, this level of accuracy is sufficient. However, there may be some requirement to measure the timing of a short activity more precisely.

An endpoint detection algorithm was developed and preliminary testing was conducted. The algorithm was based on an algorithm developed by Rabiner and Sambur for endpoint detection in speech signals [132, 188, 238].

The problems of finding endpoints in speech and accelerometry signals are analogous in many ways. In both cases the signals are time-varying and consist of periods of speech or activity (high energy signal) interspersed with periods of silence or rest (low energy signal). This is a simple problem for signals with high signal-to-noise ratios. However, it becomes significantly more difficult when the speech signals are low in level relative to the background noise, or when the background noise becomes highly nonstationary [238].

The Endpoint Detection Algorithm The activity detection algorithm (section 6.5) was used to identify periods of activity in the signal. The exact start point of the activity was deemed most likely to occur either in the first 1 s window that was classified as containing activity, or in the window immediately preceding this. Similarly, the end point was deemed most likely to occur in the last window containing activity or the first window succeeding this.

The body acceleration component of the magnitude acceleration vector, ρ_{BA}, was computed as $\rho'_{BA} = \rho - \rho'_{GA}$. This estimate was used rather than application of a filter because the ripple introduced by the filter distorts the endpoints (refer to section 5.2.7).

A threshold, th, based on the r.m.s. value was set as $th = t \times r.m.s.(\rho'_{BA})$, where t was an experimentally determined constant between 0 and 1 and $r.m.s.(\rho'_{BA})$ was the root mean square of the body acceleration magnitude vector estimate, ρ'_{BA}.

To find the start point of the activity, the two windowed periods in which the activity was determined to have commenced were considered. The algorithm began at the start of this search area and looked for the first occasion on which the magnitude of ρ'_{BA} exceeded the threshold. Since the threshold was set below the r.m.s. of ρ'_{BA}, this point must exist. This point became the first estimate of the start point. Starting from this point, the signal was searched backwards until a zero crossing was found. The sample point immediately after this zero crossing was designated the start of the activity. If a zero crossing was not detected within

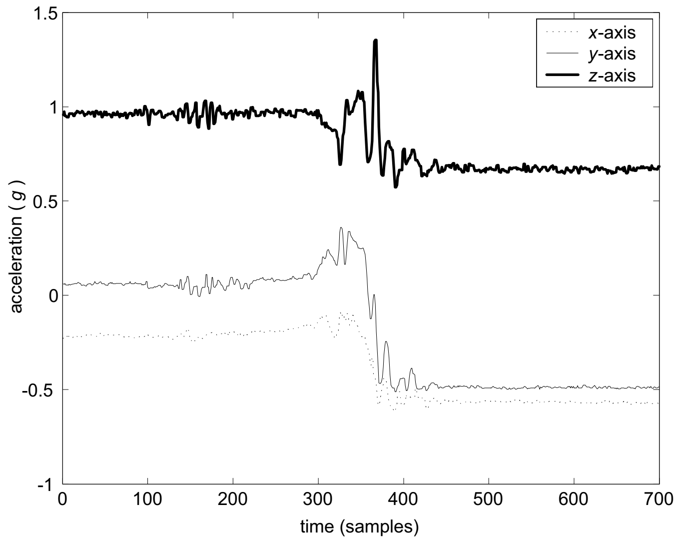

Figure 9.4: Raw acceleration signals obtained from a stand-to-sit transition.

the two window interval then the start point estimate from the activity detection algorithm was retained. The end point was then identified in the same manner. The algorithm is illustrated in figures 9.4–9.8.

Experimental Procedure A study was carried out to determine the effect of white noise on the system. The algorithm was provided with an idealised magnitude acceleration signal. This consisted of 200 samples of moving acceleration. Before and after the 200 sample period were 1000 samples, all set to 1.0. Different levels of noise were added to the signal and the accuracy of the endpoint detection algorithm was evaluated.

As a second task, a study was conducted to assess the performance of the algorithm on experimental data. The endpoint detection algorithm was applied to three data sets obtained from the TA. The first data set was obtained by placing the TA unit on a table. The unit was then lifted by the investigator, moved around briskly, and then replaced on the table. The movements were timed with a stopwatch. This produced clearly defined periods of rest and activity. This procedure was repeated 27 times. Every data sample was time stamped so that each activity could be identified on the resultant signal trace. The investigator manually identified the endpoints of each period of activity. This data formed the first data set.

The first data set was then modified to create a more idealised second data set in the following manner. Noise in the signal during periods of rest was removed by setting the magnitude vector to 1.0 g during these periods.

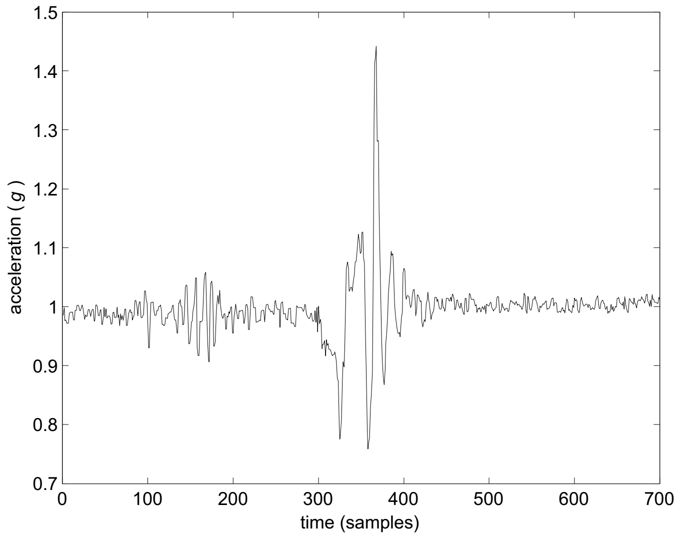

Figure 9.5: Magnitude acceleration for the stand-to-sit transition.

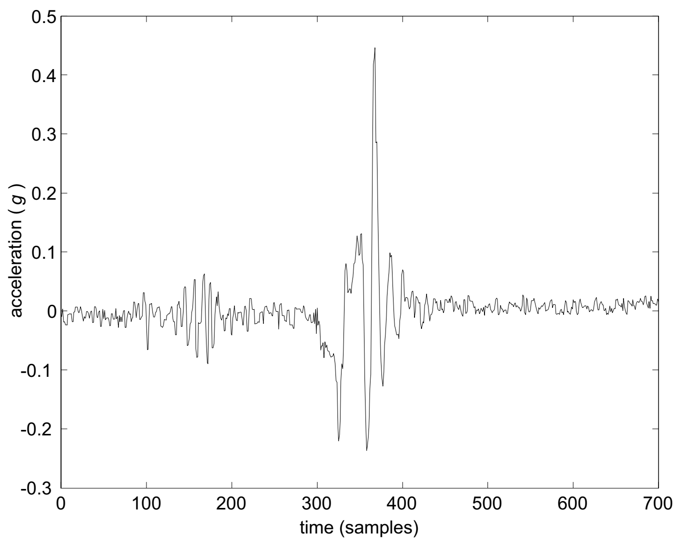

Figure 9.6: Endpoint detection, step 1: the body acceleration component estimator is computed.

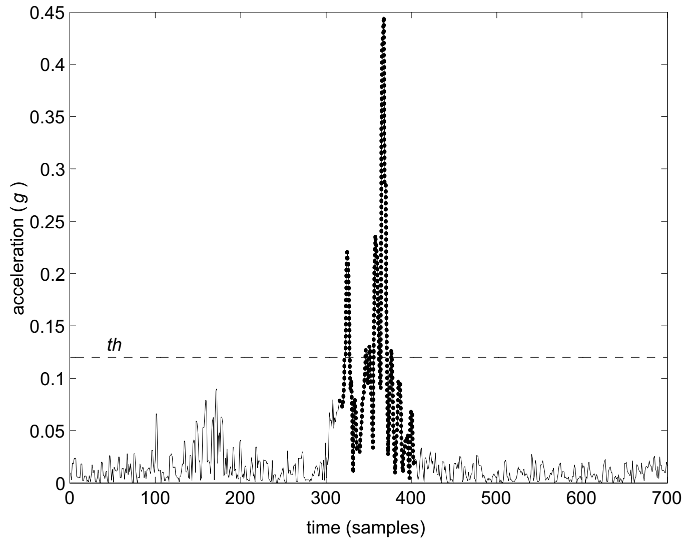

Figure 9.7: Endpoint detection, step 2: the absolute value of the body acceleration magnitude vector is computed. The period of activity is indicated. The threshold value, th, is also shown.

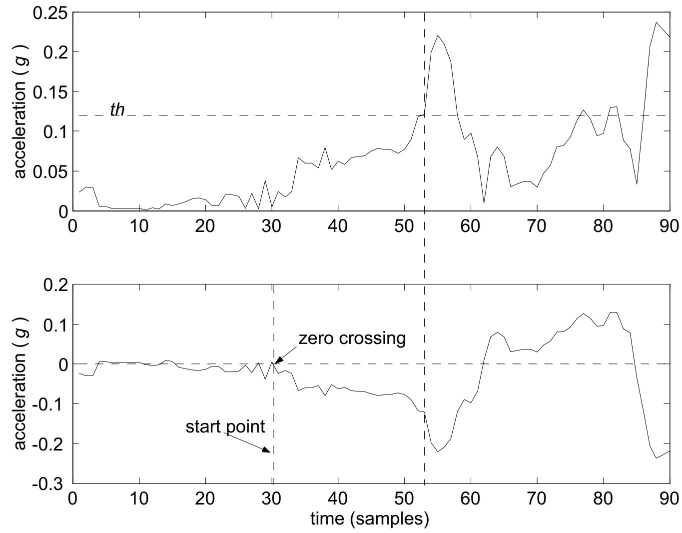

Figure 9.8: Endpoint detection, step 3: determining the start point. The point at which the absolute value of the body acceleration magnitude vector first exceeds the threshold value, th, is identified (top graph). The start point estimate is the first point before this point at which the body acceleration magnitude vector passes through 0 (bottom graph).

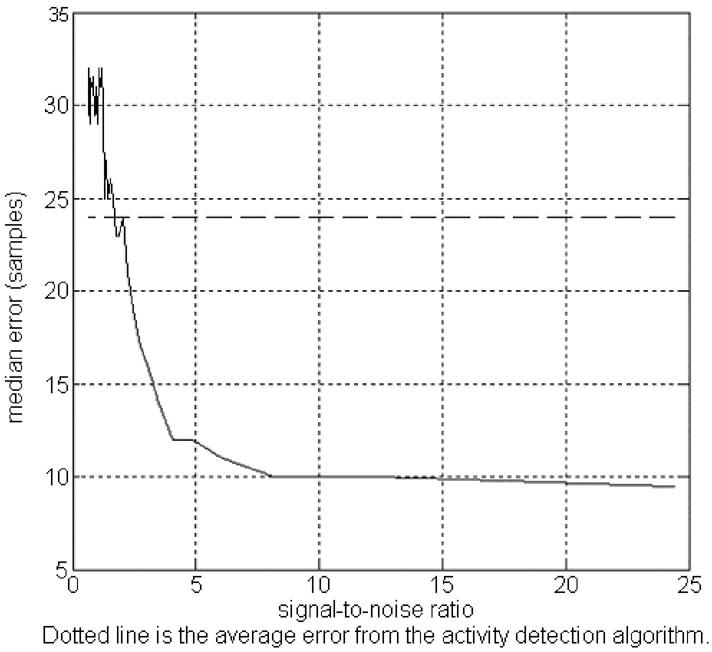

Figure 9.9: The effect of white noise on the endpoint detection algorithm. As the signal to noise ratio decreases, the error in endpoint estimate increases until the endpoints cannot be determined.

The third data set consisted of signals obtained from 26 normal subjects, each of whom performed 11 activities, being: standing up, sitting down and walking, interspersed with rest periods. The subject was directed through the procedure by an investigator who timed each activity segment using a stopwatch. Every data sample was time stamped so that each activity could be identified on the resultant signal trace. The investigator manually identified the endpoints of each period of activity.

The endpoints of each data set were calculated using the endpoint detection algorithm. For each data set, different threshold values were tested, and the three different methods of obtaining the a.c. signal were tested. The results were compared to the manually determined values.

Preliminary Results Figure 9.9 shows the effects of white noise on the detection capability of the algorithm. As the level of white noise increases, the ability of the system to identify the endpoints decreases. The algorithm became completely ineffective when the signal to noise ratio reached 1.57 and the algorithm had a detrimental effect on the endpoint estimates when the SNR was below this value.

The optimal threshold value was found to be $th = \frac{1}{3}$ (th was varied increments

median errors	data set 1	data set 2	**data set 3**
from activity detection algorithm	17	17	27
from endpoint detection algorithm	6	3	9
on start point	4	1	7
on end point	8	6	14

Table 9.1: Results of preliminary testing with the endpoint detection algorithm.

of $\frac{1}{12}$). As expected, performance was best on the idealised data of the second data set, where the median error between the estimated and the actual endpoints was only 3 samples. The median errors for each data set are shown in table 9.1. In the third data set, the standard deviation in the error when detecting the endpoints for walking was double the standard deviations for the other activities.

Discussion and Conclusion In this preliminary study the algorithm led to a mean reduction in the median endpoint error in the data set of real movements by 63%. This indicates a significant improvement in this case. However, the real measure of the quality of the algorithm is in whether or not it causes an improvement in classification accuracies. Accurate endpoint detection is not necessary for classification of upright/lying transitions, nor for the detection of walking, nor for the classification of sit/stand transitions when an expert system is used. Accurate classification is, however, necessary for comparison of activity signals using pattern matching techniques, such as are used in the dynamic time warping algorithm that is described in the next section. Thus, the utility of the endpoint detection algorithm should be evaluated in conjunction with a classification algorithm.

It may also be supposed that accurate endpoint detection would result in more accurate estimates of activity durations. However, this is not the case, because the activity durations are not measured based on specific body movement events (such as foot touches ground) but on the presence or absence of a level of movement. Thus, the measured activity durations are only approximations. They would be expected to be accurate to within 1–2 s, but not more so than this, and hence, increasing the accuracy of the endpoint detection will not actually improve the estimate of activity duration.

Classifying Unidentified Activities Using Template Matching Techniques

All periods of activity that were not explicitly classified by the classification algorithm were categorised as "other activities". However, there were large differences between the activities in this category—some were of short duration while some were of long duration, some had a low SMA while others had a high SMA, and there was a wide range of different signal patterns.

Although the actual activity performed in these movements is not known, it is possible to subclassify them into groups of similar signals. This can be useful in that it provides statistical information on the unclassified activities. It can then be seen whether a particular activity is prevalent, in which case, it may warrant more detailed examination. It can also provide an indication of the duration and level of energy expenditure in the unclassified activities.

One of the difficulties in doing this is that different instances of the same activity may yield signals of different magnitudes and durations. Moreover, the timing between the component movements of the activity may differ in different instances of the activity. In order to compare the signals from two activities, they need to be able to be normalised with respect to magnitude and duration.

Magnitude normalisation can be performed by removing the mean and dividing the signal by its root mean square, or other appropriate value. Duration normalisation can be performed by means of the nonlinear dynamic time warping (DTW) algorithm. This is a deterministic template-matching algorithm, in which a test signal is stretched in a nonlinear manner according to a set of constraints until the best possible match with a template signal is achieved. The algorithm describes the stretching and squashing that needs to be done to achieve the best match. It also provides a measure of the (mathematical) distance between the time warped test signal and the template signal. A lower distance score indicates a better match. The algorithm is described in detail by Deller *et al.* [60].

A proposed algorithm that automatically categorises the activities is as follows. The test signal is normalised in magnitude and then compared to the template for the first category using the DTW algorithm and a distance score is calculated. This procedure is repeated for all of the other categories. The category that gave the lowest distance score is chosen. If the distance score for the chosen category is less that a preset threshold then the test signal is added to this category and the category template is updated by averaging all of the signals that are contained in that category. If the distance score exceeds the preset threshold then the test signal is placed in a new category and becomes the initial template for that category.

This algorithm uses arbitrarily many adapting categories. There are several variations on this algorithm that can be performed. Firstly, the test signal could be tested against category templates only until a comparison gives a distance score that is lower than the preset threshold. This reduces the amount of processing required. Secondly, fixed categories could be used. Then the test signal is placed in the category that resulted in the lowest distance score, regardless of the value. Thirdly, fixed templates, rather than adaptive templates, could be used.

In preliminary testing, this DTW-based algorithm was applied to all of the activity data collected in the study of section 6.5, and data from early laboratory testing. The early results showed promise, although further work is required to obtain a measure of the performance of this algorithm. The performance of the algorithm is very dependent on the choice of parameters, particularly on the preset distance score threshold and work would be needed to determine suitable parameter values.

The DTW algorithm depends on receiving accurate estimates of the activity endpoints. If the endpoint estimates are too inaccurate then the test signal cannot be adequately matched to the template signal, regardless of how similar the two activities may actually be. The DTW algorithm and the endpoint detection algorithm should be evaluated together, and optimal parameters determined for the two algorithms at the same time.

Other approaches to the categorisation of unidentified activities that could be considered are hidden Markov models and self-learning neural networks. These two methods add a stochastic dimension to the decision making that may provide superior performance to the DTW algorithm. This remains to be investigated.

Extracting Simple Activities from Complex Movement Patterns

The current work focussed on the classification of simple activities; that is, activities where there was only one action performed during the period of activity. The next stage of work is to investigate the automated classification of periods of activity that incorporate multiple activities. An analogous problem has received a great deal of attention in speech processing where research has focussed on continuous speech recognition, that is, identification of the message from speech uttered in an unconstrained manner [60]. The techniques that have been used most successfully in speech processing may also be able to be applied to the signal from the TA. These include the use of hidden Markov models, formal language modelling techniques and artificial neural networks. In study 3F (sections 7.7 and 8.4), heuristic rules were used to infer the presence of a complex movement (a sit-to-stand transition followed by walking) when a sit-to-stand transition was not detected between a period of sitting and a period of walking. Future work could involve investigation of techniques to extract simple activities from complex movement patterns.

9.6 Clinical Testing

In the current work algorithms for classification of activities and postural orientations, and for the extraction of parameters, were developed and tested using cohorts of healthy subjects. The next stage of the work requires statistical validation of these algorithms for cohorts of subjects who are most likely to derive benefit from unsupervised monitoring. These include patients in rehabilitation after an illness or injury, those with a chronic disease condition, and the frail elderly. The methods that were developed in this study for falls detection and parameter extraction need to be tested in randomised trials. The hypothesis that the longitudinally tracked parameters can provide early indicators of changes in health and functional status also needs to be tested in randomised trials.

Possibilities for studies include:

- A field trial to validate the activity classification algorithms for a different subject cohort of subjects. Possible cohorts include rehabilitation patients, the frail elderly and patients with chronic disease. This study would also collect data on parameters of basic daily activities for this subject cohort. The parameter values could be compared to those obtained from the normal subject cohorts used in the current work.

- A field trial to validate the use of the system for detection of falls and predictors of falls. A cohort of at least fifty subjects would be required for a period of at least six months. The subjects would be required to be elderly, living independently at home, and to have had more than one fall in the last two years in order to maximise the likelihood of detecting fall events. In this trial, subjects would be required to wear the TA device every day. They would keep a diary to record all falls, stumbles and “turns”. In the event of a fall, stumble or “turn”, the subject would press the button on the TA to indicate the event. TA data would be recorded by the system and the results of the TA falls detection algorithm would be correlated with the falls diary and button press record. The data would be studied for anomalies that may be predictors of falls.

- A field trial to validate the use of the system for detection of early changes in health and functional status through longitudinal parameter tracking. This study would be conducted in the same manner as the unsupervised home field study (refer to section 7.8), but the subjects would be chosen from either frail elderly or housebound patients with chronic disease, whose health status is liable to change. The study would need to run for at least six months with at least fifty subjects.

9.7 Longitudinal Monitoring with an Adaptive Template

Parameters of movement were extracted from the acceleration signals during the directed routine and the periods of free movement. These parameters were stored and tracked longitudinally. It is known from the literature that changes in these parameters can indicate changes to health or functional status (refer to chapters 2 and 3).

The parameters obtained from an individual subject can be compared to population norms to provide an indication of the functional status of the subject. As more data are collected from the subject, the newly collected parameters can be compared to parameters collected earlier from the same subject to monitor change in functional status.

Changes in the parameters due to changes in health can occur abruptly or gradually over time. Abrupt changes will occur with acute illness. If, for example, a subject becomes ill with a cold, or urinary tract infection, there will be a sudden decrease in the amount of energy expended by the subject. This may be seen as a decrease in the daily SMA and proportion of time spent in activity. Gradual changes will occur with chronic illness or increasing frailty. Over a period of several months it may become apparent that a subject is performing the sit-to-stand transition more slowly and that their step-by-step gait variability is increasing, both of which indicate a declining functional status and an increase in falls risk.

As the data are collected a statistical template can be developed for the subject. Each time more data are collected, the template can be adapted by the addition of the new data. Short term and long term thresholds can be applied to the data. The newly collected parameters can be compared to the short term thresholds. If any of the thresholds are exceeded, the event can be flagged and a carer or clinician notified. The rate of change of the longitudinal trends can be compared to the long term thresholds. If any of the long term thresholds are exceeded, this event can also be flagged to indicate a gradual but marked deterioration in health status, and a carer or clinician notified.

9.8 Knowledge Management and Decision Making

The focus of the current work was on understanding and interpreting the data obtained from a waist-mounted TA during unsupervised monitoring. The next stage of work must consider the presentation and dissemination of the collected information.

Time-based trends of parameters, plotted together with normal values and template thresholds is a way to present the collected data that shows clearly the important aspects. An example of this presentation is shown in figure 9.10. In this figure the parameter values are genuine, and are taken from one of the elderly subjects involved in the unsupervised home monitoring study, but the normal and threshold values are arbitrary. In this example, the parameter value measured on day 17 exceeds the short term threshold value. In this case, this was just a statistical fluctuation (caused by the subject continuing to move after completing the transition) and none of the other parameters measured on the same day exhibited abnormal behaviour. Histograms, pie charts and other graphs can also be applied to illustrate the performance of a subject over a specified time interval (see, for example, the paper by Kiani *et al.* [123])

The time-based trends should be made available to the patient's clinician or care manager, via the Internet or any other appropriate means. In addition, regular (weekly or monthly) reports should be generated and provided to the patient's clinician or care manager (and also the patient, should she or he wish it). The report should summarise the information from the reporting period. Each item should be listed together with a rating. Possible ratings include:

- very low, low, normal, high, or very high;
- normal, or abnormal;
- much worse than last time, worse than last time, same as last time, better than last time, or much better than last time.

Any items that have changed since the last report should be highlighted.

When the monitoring system detects an abnormal event it needs to alert an appropriate person. Some of the events that need to be flagged are:

- falls in which aid is required;
- falls and stumbles in which aid is not required;

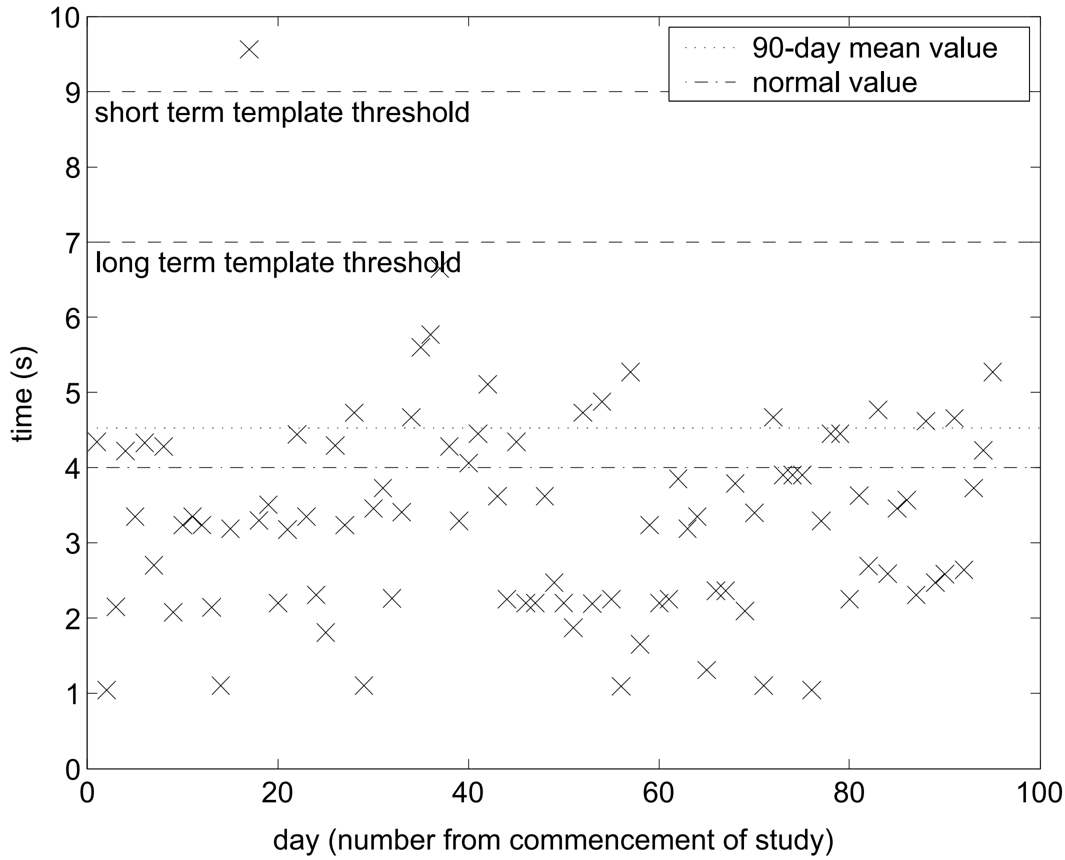

Figure 9.10: Example presentation of monitoring data. The data shown are the duration of the sit-to-stand transition. The measured parameter value for each day of the study is plotted. The 90-day mean value is shown. The normal value for the subject cohort, and the short term and long term template threshold values for the subject are shown. (The plotted values for these last three parameters are arbitrary, since this information has not been collected or determined. They are graphed merely to illustrate the data presentation method.)

- extended periods without movement (when the TA unit is being worn), regardless of the posture of the subject;
- parameter values exceeding either a short-term or a long-term threshold;
- the detection of an upside-down posture;
- large acceleration peaks; and
- faulty operation of the system.

The level of flagging will depend on the nature of the event. Events can be classified as one of three main levels:

1. Alarm generation required. This is the highest level of notification and occurs when an immediate response is required. This level is used if a fall is detected in which aid is required, or if an extended period without movement is required. The system immediately contacts an emergency carer or call centre by means of telephone, or any other appropriate means and makes them aware of the problem. The same methods that are currently used in personal alarm systems are appropriate for use here [45, 192, 237]. It is important that the system continues attempting to make contact until it knows that a person has received the message. An alert is also generated, and the event is also logged.

2. Alert generation required. This is the second level of notification and occurs after an event is detected that indicates a change in health or functional status, but in which immediate response is not required. This level is used if a fall or stumble is detected in which aid is not required, if a longitudinal template threshold is exceeded, or if faulty operation of the system is detected. A single parameter exceeding the longitudinal template threshold such as occurred in the example case above would not be sufficient to generate an alert. This would require supporting evidence from other parameter values before a decision was taken that the subject's health status had deteriorated. In the event of an alert being required, the system sends a message—by electronic mail, facsimile, or any other appropriate method—to an appropriate person—a clinician or carer, in the case of clinical changes, and a technician or carer, in the case of faulty operation—to alert them to the problem. The event is also logged.

3. Log generation required. This is the lowest level of event notification and occurs when an abnormal, but not immediately significant, event occurs. Large

acceleration peaks and upside-down postures will be logged, as will all events that require an alert or alarm to be generated. The event time and description are recorded in a log file. Appropriate people such as the patient's clinician can inspect the log file at any time, but no message is generated at the time of the event to alert them to the event. The primary purpose of the log file is to provide a record of events that can be referred to if historical information is required.

Before an alarm is generated, the patient should be notified by means of an audible message. The message should tell the patient that an alarm condition has been identified and that an alarm will be generated unless the patient cancels the alarm. If the alarm is genuine, then this message will reassure the patient that aid is being sought. If the alarm is false, then the patient has an opportunity to cancel the alarm. Alarm cancellation should only be possible from the receiver unit. All false alarms should be recorded as such.

9.9 Integration into the Health Care System

In the current work the TA system was used in isolation. However, in order to disseminate the information from the system, and to ensure that information from the system is responded to appropriately, the system needs to be integrated into the existing health care system. There are a number of ways in which this can be achieved.

Firstly, it can be used as a stand-alone, intelligent personal alarm system for falls detection. In this case, the system would need to be told who to contact in the event of an emergency, and how to contact them. Existing personal alarm systems usually contact either a 24-hour call centre or a carer by means of telephone. This TA system could do the same.

Secondly, it can be used for stand-alone monitoring of unsupervised movement. In this case, the system needs to be told who to contact in the event of an emergency, and how to contact them. Secondly, the parametric information collected by the system needs to be made available to the patient's clinician or case manager so that appropriate interventions can be taken.

Thirdly, it can be used as part of a comprehensive home telecare system and the data obtained from the ambulatory monitoring correlated with other measures of physiological and behavioural health status to provide additional information on the wellbeing of the patient.

Chapter 10

Conclusion

This thesis has investigated the hypothesis that accelerometry is a suitable technique for monitoring human movement patterns in unsupervised free-living subjects over extended periods, and that it can be used to quantitatively measure parameters that can provide clinical insight into the health status of the subject.

Previously, it has been shown that there are a number of parameters of human movement that provide an indication of the functional status of the subject. These parameters include the amount of postural sway exhibited during quiet standing, the time taken to perform a sit-to-stand transition, walking speed, and variability in the walking step rate. The functional status of a subject can be determined to be normal or impaired based on measurement of such parameters. Similar parameters have also been found to be sensitive indicators of a risk of falling.

It has also been suggested that accelerometers are suitable instruments for monitoring human movement under free-living conditions. Accelerometers have been successfully used in the measurement of energy expenditure during routine daily activities. They have also been used in the assessment of sit-to-stand transitions, gait and balance, and in systems for automatic classification of movements. Most of the assessment of particular movements has taken place inside a laboratory, and has used multiple instruments, placed at two or more locations on the body. However, no studies have investigated the utility of a single accelerometer instrument for long-term monitoring of health and functional status in an unsupervised environment.

The current work has presented a study of the use of a single triaxial accelerometer (TA) for monitoring in an unsupervised environment. For reasons of simplicity, useability and compliance, it was determined that an instrument attached to a single location on the body would be most suitable for unsupervised monitoring. A system was developed by the Biomedical Systems Laboratory at the University of New South Wales that consisted of a TA and a push button contained within a pager-like casing. The unit was designed to be clipped on to a belt or to the waist of a skirt or trousers. It sampled accelerations at 45 Hz and transmitted the data via a wireless link to a personal computer where the data were stored and analysed.

The current work determined the range of clinically useful information that could be obtained from this instrument. It began by developing a theoretical understanding of the signals from a TA, based on the physical properties of the instrument. The signal was made up of two main components, a gravitational acceleration component and a body acceleration component. The gravitational acceleration component indicated the postural orientation of the subject, while the body acceleration component described the movement of the subject. The accelerometer output signal was the vector sum of these two components. The two components overlapped one another in frequency and in time and so neither could be perfectly extracted from the signal.

A range of techniques for the approximate separation of the two components were considered. The two most successful techniques were a low pass FIR filter that was designed to have a close to optimal impulse response, which minimised the amount of ringing in the filtered signal, and a method in which the gravitational acceleration component was estimated using splines and subtracted from the magnitude acceleration signal to estimate the body acceleration component. The two methods were appropriate in different circumstances. The filtering method was more appropriate when removal of the d.c. component was important, such as in the estimation of metabolic energy expenditure. The spline method was more appropriate when distortion of signal characteristics was not acceptable, such as when accurate identification of activity endpoints was required.

Since perfect separation cannot be achieved, integration of the body acceleration component estimate does not provide accurate estimates of velocity or displacement of the movement. This was demonstrated both theoretically and in an experimental study.

The preferred placement for the TA unit was found to be on the waist above the anterior superior iliac spine. The waist was chosen because here the unit was close to the centre of mass and so could measure "whole body" movements. The placement above the iliac spine was chosen primarily for the comfort and convenience of the subject. The unit could be easily attached at this location and it was unlikely to be knocked or inconvenient while being worn. However, the exact placement of the unit in an unsupervised setting was dependent on subject preference, body shape and choice of clothing. A series of experimental studies were undertaken to determine the effect of device placement on the output signal. It was found that a simple model could be used to relate the TA signal output, TA placement and postural orientation. If two of these three measures were known then the third could be deduced by means of the model. This meant that, in an unsupervised setting, the placement of the TA could be determined from the TA signals by having the subject carry out a known routine that included a period of standing and a period of lying supine.

The same model was used to relate the signals obtained from TA units placed at different locations around the waist during sit-to-stand and stand-to-sit transitions. This meant that different instances of the transition could be directly compared, even if they were measured from different waist placements. This is important for longitudinal monitoring of parameters in unsupervised situations where the subject may change the placement of the device from day-to-day.

However, the same model could not be applied to relate signals from the more complex activity of walking. A model that has been used successfully to represent pelvic displacement during walking was adapted to predict pelvic accelerations during walking, but it failed to adequately reflect the true accelerations due to the amplification of errors within the model during the differentiation process. It was, however, found that the vertical axis acceleration signals measured from different waist placements were in phase and highly correlated. This allowed parameters of gait such as cadence and step rate variability to be measured from the TA signal from any placement on the waist. Further work is required before parameters within the gait cycle, such as single and double stance times, can be measured from the signals of a TA unit placed anywhere on the waist.

It was concluded that a system for monitoring postural orientation, sit-to-stand movements and parameters of step rate during walking can use a waist mounted TA placed above the anterior superior iliac spine and can tolerate variations in the placement position, both across subjects and for the same subject over time.

Most studies of accelerometer-estimated energy expenditure by other researchers have placed the accelerometer at the sacrum. Thus, a study was undertaken to determine the validity of using a TA placed above the right anterior superior iliac spine to estimate energy expenditure. In a study of treadmill walking at various speeds by twelve subjects, a correlation statistic exceeding 0.99 was obtained between the signal magnitude area (an estimator of metabolic energy expenditure, referred to as the SMA), measured by a sacrum mounted TA and a TA placed above the right anterior superior iliac spine. This indicated that there was an almost perfect linear relationship between the measurements at the two placements. It was concluded that energy expenditure could be measured by a TA at either location with the same degree of accuracy.

The majority of studies by other researchers that have classified movements from an accelerometer signal have developed a classifier specific to the movements of interest. In the current work, a general framework for movement classification was developed. This framework was designed to be suitable for classification of any set of movements. It was structured as a hierachical binary decision tree. At each node, a single yes/no decision was made about whether or not the section of signal in question satisfied a certain condition. If the condition was satisfied then the processing would ripple down to a lower level in the tree to make more detailed decisions until a final classification was obtained. If the condition was not satisfied then the processing would flow along to the next node at the same level in the hierachy and the process would be repeated. One algorithm was associated with every node. This made it simple to measure the accuracy of each algorithm, and to modify, add and remove algorithms. All of the algorithms were designed to be suitable for real time processing, and a combination of signal processing techniques and heuristic rules were used.

An implementation of the framework specific to the needs of unsupervised monitoring of free-living, housebound subjects was presented. This focussed on the identification of important basic movements, including lying, sitting, standing, walking, postural transitions and fall events. A suite of algorithms was developed and evaluated using data taken from normal subjects performing sequences of directed movements in a laboratory setting. These algorithms determined whether or not the TA unit was being worn; distinguished between activity and rest; distinguished between upright and lying resting states; identified lying subpostures; distinguished between sitting and standing; identified fall events; identified periods of walking and walking step rate; and identified postural transitions. Each algorithm was tested and evaluated using data taken from a cohort of healthy, normal subjects. All of the algorithms performed with better than 90% accuracy on the controlled data sets taken from normal subjects.

Once a movement was identified, movement-specific parameters could be extracted from the signal. These parameters included tilt angle, activity duration, walking speed, postural sway and energy expenditure as measured by SMA. Many of these parameters, such as sit-to-stand transition time and walking speed, have known clinical relevance as indicators of functional status. Others provide further information on the movement that may prove clinically useful when tracked longitudinally.

It was determined that there were two primary requirements in long term unsupervised monitoring of human movement. The first requirement was to identify abnormal events, such as falls, so that an alarm could be raised. The second requirement was to longitudinally track clinically sensitive parameters that were indicative of functional status. A methodology for unsupervised home monitoring of free-living subjects was designed to address these requirements. This methodology consisted of two components: a routine of directed movement from which clinically sensitive parameters were extracted and tracked longitudinally, and a period of free movement in which the TA monitored the subject's movements for falls, and recorded general parameters of movement, including energy expenditure. Each component of the system was tested systematically in a series of experimental studies.

These studies were:

- a study of directed movements in an unsupervised laboratory setting with normal, healthy subjects;
- a study of directed movements in a supervised home setting with a normal, healthy subject;
- a study of free movements in a supervised home setting with a normal, healthy subject; and
- a study of directed and free movements in an unsupervised home setting with healthy, elderly subjects.

All subjects found the system easy to use, and all reported that the TA unit was comfortable and not inconvenient to wear, although several of the elderly subjects changed the placement of the device to prevent discomfort.

The movements in the directed routine were automatically identified using a combination of button presses, the activity classification algorithm, and heuristic rules. This identified the activities and movements in every study with at least 97.8% accuracy. Overall, the results obtained showed a high degree of consistency. There were no significant differences in the sets of parameters obtained in the supervised laboratory study, the unsupervised laboratory study, and the supervised home study. Parameter values were similar for all subjects, and were also consistent within individual subjects. In every subject cohort, there were statistically significant differences between the signals from quiet standing, sitting and lying.

There were several statistically significant differences between the parameter values obtained from the healthy elderly cohort and those obtained from the healthy younger cohorts. The elderly group recorded lower SMA values and smaller acceleration ranges for most activities. They also recorded greater SMA values and acceleration ranges during the 30 s stand and during the lying period. The elderly subjects also took slightly longer to complete the sit-to-stand transition. There was no difference in the amounts of postural sway between the groups, nor were there any differences in gait cadence or variability.

No fall events occurred during any of the studies.

In the study of free movement with the elderly subjects, parameters of energy expenditure (SMA) and the proportion of time spent in activity were computed on an hourly and a daily basis. There was a strong correlation between these two parameters ($r = 0.951$) when compared on an hourly basis. A moderate negative correlation was obtained between weekly self-perceived health status and mean energy expenditure of $r = -0.507$, indicating that subjects were less active when they felt less well. This preliminary result lends support to the hypothesis that the TA unit can be used for preventative health monitoring by detecting early changes in overall health status through changes in mean SMA.

These results indicate that the waist mounted TA is a reliable instrument for monitoring movement in an unsupervised home environment, which can provide measurements of clinically significant parameters.

This work has undertaken a rigorous and systematic analysis of all of the aspects involved in using accelerometry for unsupervised monitoring in a home environment. It has found that a single waist-mounted triaxial accelerometer is a practical instrument for this purpose. It was well accepted by all subjects, including the cohort of elderly subjects who used the device daily for 2–3 months. Important movements were able to be identified from the signals. Clinically significant parameters were able to be extracted from the signals and tracked to provide a longitudinal measure of functional ability, which may, in the future be used to provide early identification of changes in functional status. Fall events, extended periods without movement and other adverse events could be identified by the device.

In conclusion, the waist mounted triaxial accelerometer has been shown to be a suitable instrument for monitoring human movement patterns in unsupervised free-living subjects over extended periods, and it can be used to quantitatively measure parameters that can provide clinical insight into the health status of the subject. This device has a great deal of potential as a low cost instrument for preventing morbidity and maintaining quality of life in community dwelling, housebound patients, by providing the security of continuous monitoring and by providing useful clinical information on the functional status of the subject in the home environment.

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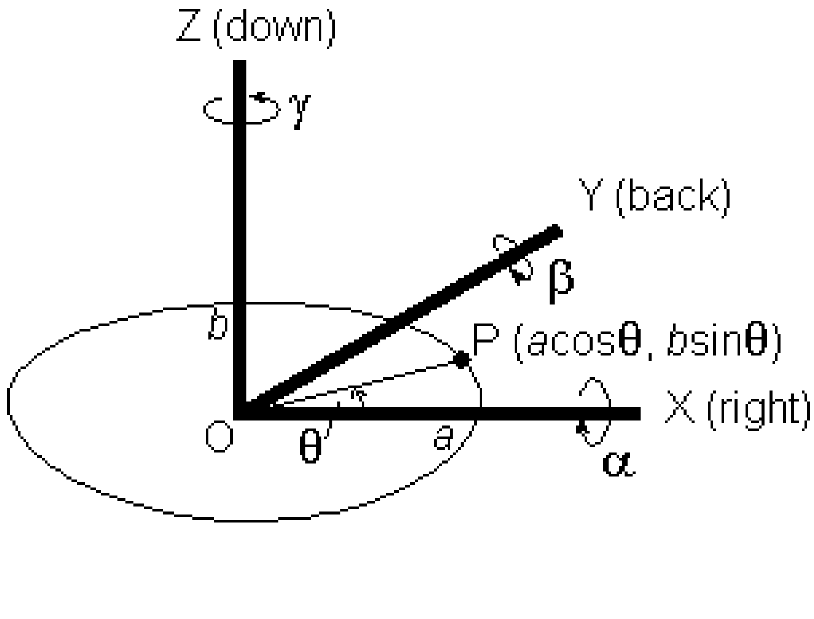
Appendix A

A Model of the Pelvis During Gait

Research has found that the displacement of the pelvis during ambulation can be accurately represented in terms of a model with six degrees of freedom. Movement in each dimension is independent and is represented by a sinusoid (refer to section 3.6.4).

The pelvis was modelled as a rigid body with an elliptical cross section, as shown in the figure.



Representation of the pelvis with six degrees of freedom of movement.

The model was described by the following equations:

$x = x_m \sin(\omega t)$ (lateral translation)
$y = -y_m t$ (forward translation)
$z = -z_m \sin(2\omega t - \frac{\pi}{2}) = z_m \cos(2\omega t)$ (vertical translation)
$\alpha = \alpha_m \sin(2\omega t - \frac{\pi}{2}) = -\alpha_m \cos(2\omega t)$ (x-axis rotation)
$\beta = \beta_m \sin(\omega t)$ (y-axis rotation)
$\gamma = \gamma_m \sin(\omega t - \frac{\pi}{2}) = -\gamma_m \cos(\omega t)$ (z-axis rotation)

where:

t is the time in seconds

ω is the angular frequency, or, in this case, $\frac{2.\pi}{\text{gait cycle period}}$, and

$x_m = 2.5\,\text{cm}, y_m = 140\,\text{cm}, z_m = 2.5\,\text{cm}, \alpha_m = 2.5°, \beta_m = 2.5°, \gamma_m = 5°$ were used as initial parameters.

In this model, all rotation is about the centre of the ellipse (assumed to be the centre of mass of the subject). From these equations, the three-dimensional position, velocity, and acceleration of any point on the ellipse at any point in time can be calculated.

The acceleration at any point on the ellipse, at any point in time is composed of the gravitational acceleration and the body movement acceleration. These can be computed separately and then added together.

Consider first the displacement of point P. The position of point P at time $t + \Delta t$ is given by rotating the position at time t through the rotations that have occurred during the period Δt. These rotations are given by:

$$\alpha = -\alpha_m \cos(2\omega\Delta t) \tag{A.1}$$
$$\beta = \beta_m \sin(\omega\Delta t) \tag{A.2}$$
$$\gamma = -\gamma_m \cos(\omega\Delta t) \tag{A.3}$$

Multiplication by rotation matrices does not commute, that is, the order in which the rotations occur is important, but if the angles of rotation are small then the operation is approximately commutative and the entire rotation can be represented by:

$$R = \begin{bmatrix} 1 & \gamma & -\beta \\ -\gamma & 1 & \alpha \\ \beta & -\alpha & 1 \end{bmatrix} = \begin{bmatrix} 1 & -\gamma_m \cos(\omega\Delta t) & -\beta_m \sin(\omega\Delta t) \\ \gamma_m \cos(\omega\Delta t) & 1 & -\alpha_m \cos(2\omega\Delta t) \\ \beta_m \sin(\omega\Delta t) & \alpha_m \cos(2\omega\Delta t) & 1 \end{bmatrix} \tag{A.4}$$

and so

$$\begin{aligned}
P(t+\Delta t) &= RP(t) \\
&= \begin{bmatrix} 1 & -\gamma_m\cos(\omega\Delta t) & -\beta_m\sin(\omega\Delta t) \\ \gamma_m\cos(\omega\Delta t) & 1 & -\alpha_m\cos(2\omega\Delta t) \\ \beta_m\sin(\omega\Delta t) & \alpha_m\cos(2\omega\Delta t) & 1 \end{bmatrix} \begin{bmatrix} a\cos(\theta) \\ b\sin(\theta) \\ 0 \end{bmatrix} \\
&= \begin{bmatrix} a\sin(\theta) - b\sin(\theta)\gamma_m\cos(\omega t) \\ a\cos(\theta)\gamma_m\cos(\omega t) + b\sin(\theta) \\ a\cos(\theta)\beta_m\sin(\omega t) + b\sin(\theta)\alpha_m\cos(2\omega t) \end{bmatrix} \qquad \text{(A.5)}
\end{aligned}$$

for small changes in angle. The gravitational acceleration thus needs to be determined incrementally.

Consider now the body movement component. If orthonormal vectors along the x-, y-, and z- axes are represented by units $\mathbf{i}$, $\mathbf{j}$, and $\mathbf{k}$ respectively then the linear displacement, velocity and acceleration are given by:

$$\begin{aligned}
\mathbf{d}_O(t) &= x_m\sin(\omega t)\mathbf{i} - \mathbf{y}_m t\mathbf{j} + z_m\cos(2\omega t)\mathbf{k} && \text{(A.6)} \\
\mathbf{v}_O(t) &= \mathbf{d}'(t) = \omega x_m\cos(\omega t)\mathbf{i} - \mathbf{y}_m\mathbf{j} + 2\omega z_m\sin(2\omega t)\mathbf{k} && \text{(A.7)} \\
\mathbf{a}_O(t) &= \mathbf{d}''(t) = -\omega^2 x_m\sin(\omega t)\mathbf{i} - \mathbf{4}\omega^2 z_m\cos(2\omega t)\mathbf{k} && \text{(A.8)}
\end{aligned}$$

and the angular displacement, velocity and acceleration are given by:

$$\begin{aligned}
\boldsymbol{\phi}(t) &= -\alpha_m\cos(2\omega t)\mathbf{i} + \beta_m\sin(\omega t)\mathbf{j} - \gamma_m\cos(\omega t)\mathbf{k} && \text{(A.9)} \\
\boldsymbol{\omega}(t) &= \boldsymbol{\phi}'(t) = 2\omega\alpha_m\sin(2\omega t)\mathbf{i} + \omega\beta_m\cos(\omega t)\mathbf{j} + \omega\gamma_m\sin(\omega t)\mathbf{k} && \text{(A.10)} \\
\boldsymbol{\alpha}(t) &= \boldsymbol{\phi}''(t) = 4\omega^2\alpha_m\cos(2\omega t)\mathbf{i} - \omega^2\beta_m\sin(\omega t)\mathbf{j} + \omega^2\gamma_m\cos(\omega t)\mathbf{k} && \text{(A.11)}
\end{aligned}$$

Then the acceleration at $P(t)$ is given by:

$$\mathbf{a}_{bP} = \mathbf{a}_O + \boldsymbol{\omega}' \times \mathbf{r}_{P|O} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \mathbf{r}_{P|O})[167] \qquad \text{(A.12)}$$

where $\mathbf{r}_{P|O}$ represents the distance from origin O to point P. This can be calculated from equation A.5.

The gravitational acceleration component can also be computed from equation A.5. Once the position of point P is known in space then the gravitational component along each TA axis can be computed simply by considering the projection of the gravitational vector on to the axis.

Once the body acceleration ($\mathbf{a}_{bP}$) and the gravitational acceleration ($\mathbf{a}_{gP}$) have been computed the acceleration seen by the TA can be calculated as the vector sum of the two, $\mathbf{a} = \mathbf{a}_{bP} + \mathbf{a}_{gP}$.

Appendix B

Subject Information and Consent Forms

This appendix contains forms for:

- the unsupervised laboratory study (2D) test procedure;
- the unsupervised laboratory study (2D) additional information;
- the unsupervised home study (4D and 4F) subject information; and
- the subject consent form.

CHI Laboratory Triaxial Accelerometer Testing
Test Procedure

New Subject
Open the log book to the first page. Select a unique user i.d. for yourself of 2 or 3 characters. This may be your initials, or anything else that you wish. Enter your chosen i.d. into the log book, together with your gender, age, height and weight.

Every time that you use the system
Turn to the next page of the log book. This is a record of all uses of the system. Add an entry with your user i.d., the date and time, and a comment if you wish.

Take a battery from the recharger and insert it into the triax. The positive terminal slides under the cover, and connects to the terminal with the red wire. Make sure that the tape on the battery is sticking out so that you can remove it when you have finished.

Clip the button onto your waist, above the right hip bone, in the location that you would wear a pager.

The computer screen should be displaying the triax start up window, and the light beside “receiving data” should be green.
Type your user i.d. into the box and click the “OK” button.
Click the “Start Test” button and follow the instructions on the test screen that appears.
When the test is complete, the test screen will automatically close.
Remove the battery from the triax and replace it in the recharger to recharge.
Replace the triax on the trolley with the rest of the system.

Note that you need to press the button on the triax for a couple of seconds before the system acknowledges the button press.

Many thanks for your help.

Unsupervised laboratory study (2D) - test procedure

CHI Laboratory Triaxial Accelerometer Testing Additional Information

Additional Information

The purpose of this testing is to have a cohort of normal subjects each perform the same routine of daily activities - sit, stand, walk and lie down - on a daily basis. This will allow the normal intra-subject variation in these activities to be measured. It will also allow more data to be collected for analysis and development of automated parameter extraction algorithms.

The test is scheduled to run for around four weeks.

The procedure is simple and should take around 3 minutes to complete.

As we are looking at repeated measures, you are asked to carry out this test each day that you are in the office. If you wish to carry out the test more than once a day, you are welcome to do so, although this is not required.

System Description
The system consists of a PC, a home clinical workstation (HCWS), a triaxial accelerometer unit (triax) and a rechargeable battery pack with 4 batteries.

The triax is worn on the waist, above the right superior anterior iliac spine. Data is transmitted to the HCWS from where it is passed into the PC and logged. No data processing is done on this machine, it will all be done by Merryn after the event. Data will be stored, and analysed, in a de-identified format.

Booting up the system
The HCWS power switch is located at the back of the unit. When the unit is functioning properly, a display showing the current date, time, temperature, light and humidity should be visible on the front of the unit. Ensure that the HCWS is turned on before booting up the PC.

The Hetemis software system should start up automatically when the PC starts. If it does not, there is a shortcut icon (a red robot) in the middle of the screen which will start the system.

The Hetemis screen should appear with two windows in it. One is the HCWS program selector. This is necessary for proper functioning, but it can be minimised as no interaction with it is required. The other is the triax window. This window should be maximised.

The Log Book
A log book is located with the system.
The first page of this log book contains a list of users. To add yourself as a new user, simply add a unique user name to the list (this is a unique i.d. of 2 or 3

characters, for example your initials, or a number, or something that you will remember), and complete the details of your gender, age, height and weight.

The following pages of the log book are a list of system use. Each time that you complete a test, simply add your i.d. and the date and time to the log book.

Preparing the triax
To commence the testing, select a battery from the recharger and place it into the triax. The positive terminal should go under the cover (and connect to the terminal with the red wire). Make sure that the tape on the battery is sticking out when you do this : it is very difficult to remove the batteries without the tape to pull on. There is no need to place the battery cover on the unit.

Clip the battery unit onto your waist, above the right hip. If you are wearing a belt, clip it onto your belt. If you are wearing trousers or a skirt, clip it to the top of your clothing. If you are wearing a dress, toga or other clothing that renders this impossible, use the belt that is located on the trolley.

The system runs on normal AA batteries. The 4 rechargeables supplied should be more than sufficient for the duration of this test.

Ready to start testing
In the triax window you should see green lights beside the "Receiving Data" and "storing data" labels. These indicate that the system is functioning correctly. If there are no green lights, check the following:

1) HCWS is on
2) try changing the battery

Once you have the two green lights, you are ready to go.

Testing procedure
Enter your I.D. into the box, and click the "OK" button. A "start" button and a "cancel" button will appear. If the i.d. that is displayed is correct and you are ready to start the test, press the "start" button. Otherwise, press the "cancel" button to start again.

A new window will appear. Drag this window out of the way so that you can still see the original window. This allows you to watch the green lights to ensure that all is in order.

The instructions on the new window ask you to press the button on the triax to start the testing. When you do so, you should see a red light beside the "alarm" label appear on the original window.

The test will start. You will be asked to stand for 30s, then to sit down, and press the button when you are seated. It is important to sit down first, and to press the button only once you are completely settled in your seat. The button presses are used as an aid to indicate the completion of a movement.

Once you are seated you will remain sitting for 5 seconds and then be asked to stand up, then to press the button once you are properly standing. After 5 seconds you will be asked to walk around a pre-determined route. It is important that you use the same route every time, and that you walk normally around the route, not stopping to talk or taking detours, because the time taken to walk the route is one of the parameters to be measured.

Once you have returned from the walk you will be asked to press the button, and then to lie down. Once you are lying down, you again press the button, remain lying for 5 seconds, and then stand up again.

This completes the testing, and the test screen will automatically close after 10 seconds.

The test can be cancelled at any time by clicking the “Stop Test” button

Remove the battery from the triax and replace it in the battery charger to allow it to recharge.

Problems with the system (a note from Merryn)
This system was designed and implemented by me (Merryn). I will be away from 20th May until 10th June. I have tested this system as well as I can, and everything is in good working order as I leave it. However, should something goes wrong with the system that cannot be solved while I am away, just turn off the system and ignore it until I return. This includes failure of the triax - the system has been calibrated for the triax that came with the system, and so it cannot be replaced without rendering all of the results invalid.

Many thanks for your help.

ApprovalNo:..................

THE UNIVERSITY OF NEW SOUTH WALES
SYDNEY · 2052 · AUSTRALIA

THE UNIVERSITY OF NEW SOUTH WALES

SUBJECT INFORMATION STATEMENT AND CONSENT FORM

Home Monitoring with a Triaxial Accelerometer

You *(i.e. the subject)* are invited to participate in a study on ambulatory monitoring using a small, pager-sized device called a triaxial accelerometer. We *(i.e. the investigators)* hope to evaluate the device in terms of its usability and its medical benefit. Your acceptance of the system will also be evaluated.

You were selected as a possible participant because the study focuses on elderly patients living at home.

The study will be conducted over a period of up to 13 weeks. The triaxial accelerometer will measure and record how well you are able to walk and move around. It is hoped that this data will be used to identify falls, stumbles and poor mobility within the home and to eventually be used as a means for assessing patient progress and for understanding and preventing falls.

If you decide to participate, you will be given a triaxial accelerometer and a personal computer. You will be required to wear the triaxial accelerometer device each day for the duration of the trial. A researcher from the university will visit your home to set up the monitoring system. The data collected by the triaxial accelerometer will be transmitted to the computer where it will be stored until it is collected by a researcher from the university. A researcher from the university will visit your home each week to collect the data that has been stored by the system.

At the commencement and conclusion of the study we may require you to complete an assessment of your balance and fall risk, and may ask for information on your relevant medical history.

No computer experience is required in order to use the system or participate in the trial. The system has been specifically designed to be very simple to use. At the time of installation you will receive full training in the operation of the system. A technical support line will be available to you for the duration of the study should you have any difficulty with this system. All the equipment and its installation will be provided to you free of charge.

For the duration of the study, you will be required to attach the triaxial accelerometer to your waist belt when you get up in the morning. You will then need to carry out a short procedure which will take several minutes and will involve lying on the bed, sitting, standing and walking. You will then be required to wear the triaxial accelerometer throughout the day until you go to bed, except when bathing or showering. Once a week you will be asked to complete a short questionnaire on your health. This questionnaire will take around five minutes to complete. Once during the trial, and at the conclusion of the trial you will be asked to complete a questionnaire on your opinion of the triaxial accelerometer device. This questionnaire will take about fifteen minutes to complete. You will be asked to keep a falls diary. If at any stage during the study you fall, nearly fall, or stumble, you are requested to make a note of this in the diary.

Unsupervised home study - subject information, page 1 of 2

THE UNIVERSITY OF NEW SOUTH WALES

SUBJECT INFORMATION STATEMENT AND CONSENT FORM

Home Monitoring with a Triaxial Accelerometer

Possible inconveniences using the Home Telecare System may include having to fulfill the tasks for this study as stated above. Technical issues or problems may also arise from the use of this system for which you may need to contact our technical support line or we may need to contact you.

It must be stressed that this system is under trial and therefore we cannot and do not guarantee or promise that you will receive any benefits from this study. Furthermore, this system should not be viewed as a substitute for your existing management procedures. If you have any concerns about your condition during the study you should consult your doctor/hospital as you would normally.

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission or except as required by law. If you give us your permission by signing this document, we plan to publish the results of the study in academic journals. The results to be published will be your perceptions of the system, the reliability of the system and the usefulness of the device for home monitoring. In any publication, information will be provided in such a way that you cannot be identified.

Your decision whether or not to participate is entirely voluntary and will not prejudice your future relations with the University of New South Wales. If you decide to participate, you are free to withdraw your consent and to discontinue participation at any time without penalty or prejudice.

While the purpose of this trial is to evaluate the triaxial accelerometer in terms of its usability and its medical benefit, you should be aware that in the future, parts of the technology that you are using may be modified for incorporation into products for the purpose of making a medical device for commercial gain.

Should you wish to participate, you should indicate this to Anne Tiedemann (who gave you this form). Anne will inform the research team at the University of New South Wales. Ms Merryn Mathie (from the University of New South Wales) will then contact you about participating in the study.

If you have any questions, please feel free to ask us. If you have any additional questions later, Merryn Mathie (phone 9385 5316) will be happy to answer them.

Complaints may be directed to the Ethics Secretariat, University of New South Wales, SYDNEY 2052 AUSTRALIA (phone 9385 4234, fax 9385 6648, email ethics.sec@unsw.edu.au).

You will be given a copy of this form to keep.

THE UNIVERSITY OF NEW SOUTH WALES

SUBJECT INFORMATION STATEMENT AND CONSENT FORM

Home Monitoring with a Triaxial Accelerometer

You are making a decision whether or not to participate. Your signature indicates that, having read the information provided above, you have decided to participate.

Signature of subject	Signature of witness
______________________________________	______________________________________
Please PRINT name	Please PRINT name
______________________________________	______________________________________
Date	Nature of Witness
______________________________________	______________________________________

Signature(s) of investigator(s)

____

Please PRINT Name

____

REVOCATION OF CONSENT

I hereby wish to **WITHDRAW** my consent to participate in the research proposal described above and understand that such withdrawal **WILL NOT** jeopardise any treatment or my relationship with the University of New South Wales *(Hospital or my medical attendants)*.

Signature	Date
______________________________________	______________________________________

Please PRINT name

____

The section for Revocation of Consent should be forwarded to Merryn Mathie (Biomedical Systems Laboratory, UNSW Sydney NSW 2052, fax: (02) 9385 5316).

Subject consent form

Appendix C

Health Questionnaires and Assessment Forms

This appendix contains forms for:

- the Stanford Health Assessment Questionnaire disability index and pain scale;
- the medical history questionnaire; and
- the coop/wonca health questionnaire.

HEALTH ASSESSMENT QUESTIONNAIRE©
Stanford University School of Medicine
Division of Immunology & Rheumatology

Name_______________________________ **Date**_______________

In this section we are interested in learning how your illness affects your ability to function in daily life. Please feel free to add any comments on the back of this page.

Please check the response which best describes your usual abilities OVER THE PAST WEEK:

	Without ANY difficulty 0	With SOME difficulty 1	With MUCH difficulty 2	UNABLE to do 3
DRESSING & GROOMING				
Are you able to:				
-Dress yourself, including tying shoelaces and doing buttons?	☐	☐	☐	☐
-Shampoo your hair?	☐	☐	☐	☐
ARISING				
Are you able to:				
-Stand up from a straight chair?	☐	☐	☐	☐
-Get in and out of bed?	☐	☐	☐	☐
EATING				
Are you able to:				
-Cut your meat?	☐	☐	☐	☐
-Lift a full cup or glass to your mouth?	☐	☐	☐	☐
-Open a new milk carton?	☐	☐	☐	☐
WALKING				
Are you able to:				
-Walk outdoors on flat ground?	☐	☐	☐	☐
-Climb up five steps?	☐	☐	☐	☐

Please check any AIDS OR DEVICES that you usually use for any of these activities:

☐ Cane
☐ Walker
☐ Crutches
☐ Wheelchair
☐ Devices used for dressing (button hook, zipper pull, lo shoe horn, etc.)
☐ Built up or special utensils
☐ Special or built up chair
☐ Other (Specify:____________)

Please check any categories for which you usually need HELP FROM ANOTHER PERSON:

☐ Dressing and Grooming
☐ Arising
☐ Eating
☐ Walking

Please check the response which best describes your usual abilities **OVER THE PAST WEEK:**

	Without ANY difficulty 0	With SOME difficulty 1	With MUCH difficulty 2	UNABLE to do 3
HYGIENE				
Are you able to:				
-Wash and dry your body?	☐	☐	☐	☐
-Take a tub bath?	☐	☐	☐	☐
-Get on and off the toilet?	☐	☐	☐	☐
REACH				
Are you able to:				
-Reach and get down a 5-pound object (such as a bag of sugar) from just above your head?	☐	☐	☐	☐
-Bend down to pick up clothing from the floor?	☐	☐	☐	☐
GRIP				
Are you able to:				
-Open car doors?	☐	☐	☐	☐
-Open jars which have been previously opened?	☐	☐	☐	☐
-Turn faucets on and off?	☐	☐	☐	☐
ACTIVITIES				
Are you able to:				
-Run errands and shop?	☐	☐	☐	☐
-Get in and out of a car?	☐	☐	☐	☐
-Do chores such as vacuuming or yardwork	☐	☐	☐	☐

Please check any AIDS OR DEVICES that you usually use for any of these activities:

- ☐ Raised toilet seat
- ☐ Bathtub seat
- ☐ Jar opener (for jars previously opened)
- ☐ Bathtub bar
- ☐ Long-handled appliances for reach
- ☐ Long-handled appliances in bathroom
- ☐ Other (Specify:__________)

Please check any categories for which you usually need HELP FROM ANOTHER PERSON:

- ☐ Hygiene
- ☐ Reach
- ☐ Gripping and opening things
- ☐ Errands and chores

Stanford Health Assessment Questionnaire, page 2 of 3

We are also interested in learning whether or not you are affected by pain because of your illness.

How much pain have you had because of your illness IN THE PAST WEEK:

PLACE A VERTICAL (|) MARK ON THE LINE TO INDICATE THE SEVERITY OF THE PAIN

NO PAIN 0 ———————————————————— SEVERE PAIN 100

1. Have you participated in any clinical trials in the **PAST 6 MONTHS?**
   - ☐ No
   - ☐ Yes - trial of an arthritis medicine   Name of medicine ___________
   - ☐ Yes - trial of another type of medicine   Name of medicine ___________
   - ☐ Don't know the name of the medicine
2. In general, would you say your current health is:

   ☐ Excellent ☐ Very Good ☐ Good ☐ Fair ☐ Poor

SYMPTOMS

1. Please check any items which apply to your health during the **PAST 6 MONTHS**. **If *none*, check here:** ☐

HEAD, EYES, EARS, NOSE, MOUTH AND THROAT:
- ☐ Blurred vision
- ☐ Ringing in ears
- ☐ Hearing difficulties
- ☐ Mouth sores
- ☐ Loss, change in taste
- ☐ Headache
- ☐ Dizziness
- ☐ Fever

CHEST, LUNGS AND HEART
- ☐ Chest pain
- ☐ Shortness of breath
- ☐ Wheezing (asthma)

GASTROINTESTINAL TRACT:
- ☐ Loss of appetite
- ☐ Nausea
- ☐ Heartburn
- ☐ Indigestion or belching
- ☐ Pain or discomfort in upper abdomen(stomach)
- ☐ Liver problems, kind_____________________
- ☐ Pain or cramps in lower abdomen (colon)
- ☐ Diarrhea (frequent, explosive watery bowel movements, severe)
- ☐ Constipation
- ☐ Black or tarry stools (not from iron)
- ☐ Vomiting

MUSCULOSKELETAL:
- ☐ Joint pain
- ☐ Joint swelling
- ☐ Low back pain
- ☐ Muscle pain
- ☐ Neck pain
- ☐ Weakness of muscles
- ☐ If you are stiff in the morning

____(hr/min) how long does the stiffness last?

NEUROLOGIC AND PSYCHOLOGIC
- ☐ Depression
- ☐ Insomnia
- ☐ Nervousness
- ☐ Tiredness (Fatigue)
- ☐ Trouble thinking or remembering

SKIN:
- ☐ Easy bruising
- ☐ Hives or welts
- ☐ Itching
- ☐ Rash

FEMALES ONLY - ☐ Are you pregnant?

OTHER
- ☐ Any others? (specify)_____

Stanford Health Assessment Questionnaire, page 3 of 3

University of New South Wales – Triaxial Accelerometer Field Study
Medical History Questionnaire

Name: ______________________ **Date:** __________________

Gender: M/F
Date of birth:

Medical History
Describe any significant medical illnesses/conditions

Neurological

- ❑ Strokes
- ❑ Parkinson’s Disease
- ❑ Seizures
- ❑ Middle Ear Problems

Cardiovascular

- ❑ Arrhythmia or heart attack
- ❑ Valve Disease
- ❑ Rhythm problems

Blood Pressure

- ❑ High blood pressure
- ❑ Low blood pressure

Metabolic

- ❑ Thyroid disease – over/under
- ❑ Diabetes
- ❑ Anaemia

Musculoskeletal

- ❑ Rheumatoid arthritis
- ❑ Osteoarthritis
- ❑ Osteoporosis
- ❑ Back pain / injury
- ❑ Foot disorders

Psychological Disorders

- ❑ Depression / Anxiety

Visual problems

Alcohol History

Current:

Past:

Medical history questionnaire, page 1 of 2

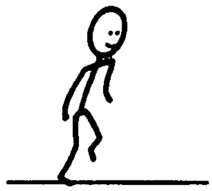
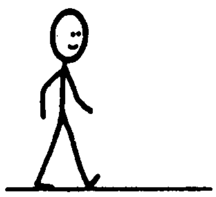
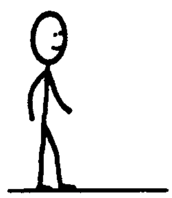
University of New South Wales – Triaxial Accelerometer Field Study
Medical History Questionnaire

Medication History
List of regular medications:

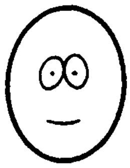
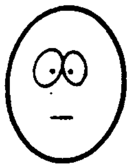
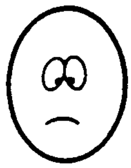
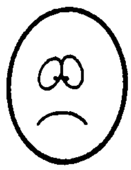
- ❑ Sedatives
- ❑ Blood pressure tablets
- ❑ Pain tablets
- ❑ Anti-epileptics
- ❑ Antidepressants

Physical fitness

During the past week…
What was the hardest physical activity you could do for at least 2 minutes?

Very heavy, (for example) run, at fast pace		**1**
Heavy, (for example) jog, at a slow pace		**2**
Moderate, (for example) walk, at a fast pace		**3**
Light, (for example) walk, at a medium pace		**4**
Very light, (for example) walk, at a slow pace or not able to walk		**5**

During the past week...
How much have you been bothered by emotional problems such as feeling anxious, depressed, irritable or downhearted and sad?

Not at all		**1**
Slightly		**2**
Moderately		**3**
Quite a bit		**4**
Extremely		**5**

Daily activities

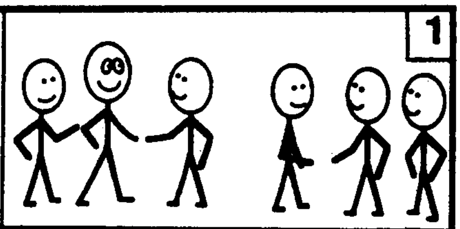
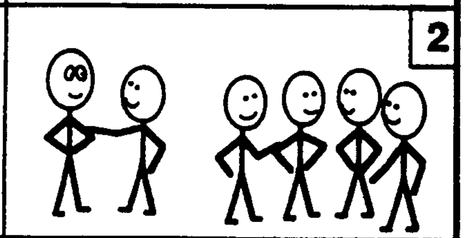
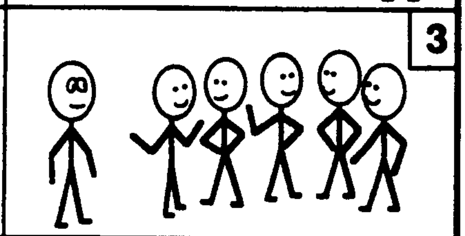
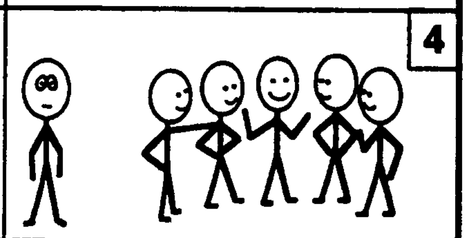
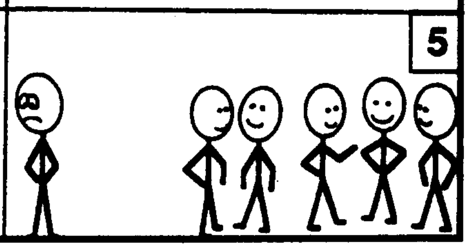
During the past week...
How much difficulty have you had doing your usual activities or tasks, both inside and outside the house because of your physical and emotional health?

No difficulty at all		**1**
A little bit of difficulty		**2**
Some difficulty		**3**
Much difficulty		**4**
Could not do		**5**

coop/wonca health questionnaire, page 3 of 6

Social activities

During the past week…
Has your physical an emotional health limited your social activities with family, friends, neighbours or groups?

Not at all	
Slightly	
Moderately	
Quite a bit	
Extremely	

Changes in health

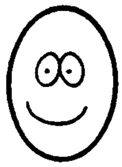
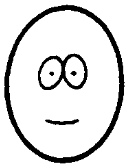
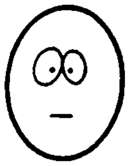
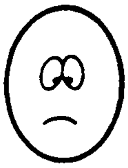
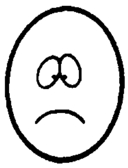
How would you rate your overall health now compared to 1 week ago?

Much better	↑↑ ++	1
A little better	↑ +	2
About the same	⇐⇒ =	3
A little worse	↓ −	4
Much worse	↓↓ −−	5

coop/wonca health questionnaire, page 5 of 6

Overall health

During the past week…
How would you rate your health in general?

Excellent		1
Very good		2
Good		3
Fair		4
Poor		5

Name: ______________________________

Short Form Physiological Assessment

The first value in the parentheses to the right of the entry box is the default value that should be used if the patient could not perform the test. The second value is the average value for the test (in case of equipment failure).

1. Edge Contrast sensitivity (MET)

Score		(1)

2. Reaction Time -Hand

	Trial 1	Trial 2	
score 1			(360 - 244)
score 2			(360 - 244)
score 3			(360 - 244)
score 4			(360 - 244)
score 5			(360 - 244)
score 6			(360 - 244)
score 7			(360 - 244)
score 8			(360 - 244)
score 9			(360 - 244)
score 10			(360 - 244)

3. Proprioception

score 1		(6 - 1.5)
score 2		(6 - 1.5)
score 3		(6 - 1.5)
score 4		(6 - 1.5)
score 5		(6 - 1.5)

4. Knee extension (quads)

Dominant Leg		(kg) (5 - 20.1)

5. Balance

Sway on foam eyes open

Anterior/posterior		mm (50)
Lateral		mm (50)

Short form physiological assessment for falls risk

Appendix D

Parametric Data from Study 2D

mvt	median	mean	s.d.	min	max
sway					
1	0	0	0	0	0
tilt (deg)					
1	14.991	14.261	6.875	0.000	34.956
3	16.684	17.623	7.557	0.000	34.951
5	15.323	14.286	6.966	0.000	36.423
6	14.443	13.648	7.423	0.000	36.261
7	15.954	14.617	6.651	-1.000	27.300
9	87.910	84.558	14.978	-1.000	106.644
11	32.904	34.921	15.654	-1.000	60.510
duration (s)					
1	30.700	32.602	5.274	27.740	48.060
2	3.410	4.415	3.029	2.140	23.390
3	7.970	9.957	12.007	4.120	102.980
4	2.150	2.632	0.829	1.040	5.550
5	8.570	10.664	5.923	5.170	33.070
6	23.840	25.671	5.715	7.530	42.300
7	7.520	8.366	4.051	-1.000	31.420

mvt	median	mean	s.d.	min	max
duration (s)					
8	5.820	6.019	1.449	-1.000	9.830
9	6.430	6.975	3.911	-1.000	26.590
10	6.430	6.508	1.563	-1.000	11.750
11	14.340	13.618	3.113	-1.000	19.550
SMA (g)					
1	0.019	0.023	0.010	0.014	0.063
2	0.281	0.284	0.062	0.181	0.473
3	0.055	0.056	0.014	0.029	0.101
4	0.280	0.278	0.042	0.189	0.430
5	0.042	0.044	0.016	0.018	0.098
6	0.379	0.379	0.064	0.197	0.515
7	0.059	0.046	0.133	-1.000	0.106
8	0.371	0.354	0.182	-1.000	0.543
9	0.072	0.058	0.135	-1.000	0.130
10	0.350	0.360	0.192	-1.000	0.639
11	0.173	0.160	0.166	-1.000	0.392

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 2D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 1 of 6.

mvt	median	mean	s.d.	min	max
median x (g)					
1	-0.092	-0.097	0.141	-0.446	0.209
2	-0.110	-0.095	0.158	-0.395	0.328
3	-0.234	-0.236	0.144	-0.560	0.144
4	-0.095	-0.092	0.152	-0.417	0.213
5	-0.077	-0.083	0.136	-0.498	0.209
6	-0.072	-0.081	0.118	-0.381	0.195
7	-0.075	-0.094	0.174	-1.000	0.197
8	-0.438	-0.395	0.242	-1.000	0.005
9	-0.692	-0.616	0.228	-1.000	0.053
10	-0.224	-0.278	0.220	-1.000	0.203
11	-0.054	-0.055	0.196	-1.000	0.378
mean x (g)					
1	-0.092	-0.096	0.139	-0.450	0.215
2	-0.100	-0.090	0.140	-0.396	0.234
3	-0.231	-0.236	0.143	-0.562	0.137
4	-0.086	-0.082	0.143	-0.347	0.315
5	-0.072	-0.081	0.135	-0.491	0.205
6	-0.074	-0.079	0.122	-0.380	0.173
7	-0.073	-0.091	0.172	-1.000	0.188
8	-0.360	-0.349	0.156	-1.000	-0.104
9	-0.692	-0.617	0.227	-1.000	0.052
10	-0.301	-0.296	0.145	-1.000	0.027
11	0.079	0.043	0.214	-1.000	0.364
standard deviation x (g)					
1	0.016	0.021	0.016	0.005	0.075
2	0.167	0.174	0.052	0.092	0.381
3	0.019	0.024	0.016	0.008	0.102
4	0.146	0.146	0.038	0.079	0.234
5	0.026	0.027	0.014	0.006	0.068
6	0.129	0.131	0.019	0.086	0.178

mvt	median	mean	s.d.	min	max
standard deviation x (g)					
7	0.021	0.012	0.129	-1.000	0.129
8	0.335	0.305	0.187	-1.000	0.484
9	0.010	-0.004	0.126	-1.000	0.036
10	0.337	0.315	0.188	-1.000	0.589
11	0.262	0.244	0.214	-1.000	0.613
max x (g)					
1	0.020	0.015	0.154	-0.317	0.360
2	0.251	0.269	0.181	-0.119	0.717
3	-0.163	-0.155	0.164	-0.501	0.398
4	0.170	0.196	0.169	-0.187	0.724
5	0.005	0.023	0.153	-0.397	0.449
6	0.322	0.361	0.237	-0.024	1.571
7	0.011	-0.001	0.182	-1.000	0.351
8	0.289	0.273	0.242	-1.000	0.963
9	-0.645	-0.577	0.233	-1.000	0.088
10	0.387	0.400	0.309	-1.000	1.376
11	0.665	0.718	0.508	-1.000	2.670
min x (g)					
1	-0.172	-0.173	0.157	-0.518	0.174
2	-0.417	-0.425	0.172	-0.909	0.050
3	-0.320	-0.317	0.145	-0.726	0.097
4	-0.320	-0.316	0.165	-0.806	0.074
5	-0.187	-0.171	0.152	-0.587	0.121
6	-0.511	-0.495	0.151	-0.882	-0.081
7	-0.161	-0.176	0.173	-1.000	0.124
8	-1.003	-1.078	0.302	-1.898	-0.647
9	-0.716	-0.659	0.221	-1.004	0.029
10	-0.828	-0.857	0.135	-1.187	-0.589
11	-0.446	-0.642	0.679	-3.739	0.150

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 2D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 2 of 6.

mvt	median	mean	s.d.	min	max	mvt	median	mean	s.d.	min	max
range x (g)						mean y (g)					
1	0.171	0.188	0.119	0.032	0.523	7	0.134	0.103	0.190	-1.000	0.456
2	0.663	0.694	0.220	0.322	1.626	8	-0.262	-0.272	0.147	-1.000	-0.015
3	0.128	0.162	0.124	0.044	0.778	9	-0.655	-0.691	0.160	-1.000	-0.316
4	0.497	0.512	0.147	0.271	0.955	10	-0.199	-0.200	0.160	-1.000	0.071
5	0.190	0.194	0.121	0.033	0.885	11	0.126	0.108	0.185	-1.000	0.344
6	0.832	0.856	0.219	0.558	2.086	standard deviation y (g)					
7	0.148	0.160	0.172	-1.000	0.606	1	0.013	0.019	0.018	0.004	0.109
8	1.239	1.335	0.457	-1.000	2.258	2	0.167	0.178	0.060	0.052	0.369
9	0.065	0.067	0.145	-1.000	0.247	3	0.019	0.025	0.019	0.007	0.133
10	1.221	1.241	0.404	-1.000	2.379	4	0.146	0.144	0.036	0.061	0.247
11	1.150	1.345	0.963	-1.000	4.646	5	0.023	0.026	0.013	0.006	0.066
median y (g)						6	0.145	0.150	0.037	0.080	0.244
1	0.109	0.084	0.137	-0.346	0.355	7	0.020	0.009	0.129	-1.000	0.125
2	0.100	0.096	0.151	-0.281	0.406	8	0.418	0.407	0.206	-1.000	0.690
3	-0.063	-0.056	0.128	-0.329	0.240	9	0.009	-0.004	0.126	-1.000	0.051
4	0.120	0.113	0.140	-0.283	0.477	10	0.402	0.413	0.213	-1.000	0.695
5	0.117	0.111	0.137	-0.163	0.489	11	0.162	0.162	0.174	-1.000	0.388
6	0.103	0.093	0.117	-0.220	0.375	max y (g)					
7	0.132	0.100	0.192	-1.000	0.458	1	0.203	0.189	0.176	-0.263	0.761
8	-0.335	-0.302	0.277	-1.000	0.205	2	0.519	0.484	0.233	-0.075	1.070
9	-0.658	-0.692	0.160	-1.000	-0.338	3	0.006	0.015	0.152	-0.255	0.630
10	-0.142	-0.159	0.264	-1.000	0.308	4	0.404	0.395	0.151	0.000	0.729
11	0.117	0.099	0.188	-1.000	0.472	5	0.220	0.221	0.141	-0.077	0.558
mean y (g)						6	0.646	0.653	0.278	0.189	1.519
1	0.110	0.085	0.136	-0.345	0.353	7	0.224	0.202	0.207	-1.000	0.529
2	0.096	0.096	0.139	-0.277	0.321	8	0.495	0.487	0.270	-1.000	1.047
3	-0.065	-0.055	0.128	-0.326	0.227	9	-0.624	-0.648	0.168	-1.000	-0.206
4	0.101	0.113	0.126	-0.186	0.423	10	0.625	0.700	0.468	-1.000	2.061
5	0.121	0.113	0.134	-0.157	0.482	11	0.541	0.535	0.289	-1.000	1.116
6	0.115	0.111	0.126	-0.239	0.418						

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 2D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 3 of 6.

mvt	median	mean	s.d.	min	max
min y (g)					
1	0.014	0.006	0.148	-0.482	0.261
2	-0.226	-0.240	0.165	-0.785	0.143
3	-0.163	-0.137	0.129	-0.507	0.183
4	-0.132	-0.129	0.129	-0.395	0.195
5	0.043	0.022	0.145	-0.332	0.358
6	-0.281	-0.287	0.169	-0.834	0.017
7	0.066	0.023	0.183	-1.000	0.421
8	-1.000	-1.049	0.304	-2.322	-0.682
9	-0.692	-0.732	0.161	-1.060	-0.372
10	-0.785	-0.845	0.192	-1.344	-0.436
11	-0.344	-0.480	0.491	-1.935	0.235
range y (g)					
1	0.141	0.183	0.145	0.026	0.878
2	0.673	0.724	0.274	0.251	1.573
3	0.135	0.153	0.095	0.040	0.719
4	0.527	0.523	0.142	0.249	0.831
5	0.189	0.198	0.119	0.034	0.854
6	0.908	0.940	0.278	0.497	1.729
7	0.160	0.164	0.177	-1.000	0.596
8	1.550	1.521	0.501	-1.000	2.835
9	0.063	0.068	0.147	-1.000	0.298
10	1.427	1.529	0.630	-1.000	3.277
11	1.045	0.999	0.569	-1.000	2.260
median z (g)					
1	0.965	0.962	0.031	0.820	1.006
2	0.942	0.930	0.055	0.602	0.997
3	0.954	0.946	0.040	0.821	1.004
4	0.954	0.946	0.039	0.798	1.012
5	0.965	0.963	0.033	0.805	1.004
6	0.963	0.956	0.037	0.798	1.020

mvt	median	mean	s.d.	min	max
median z (g)					
7	0.963	0.931	0.245	-1.000	1.003
8	0.616	0.529	0.289	-1.000	0.949
9	0.037	0.053	0.222	-1.000	0.534
10	0.711	0.656	0.268	-1.000	0.927
11	0.948	0.891	0.258	-1.000	0.998
mean z (g)					
1	0.966	0.962	0.031	0.820	1.005
2	0.934	0.924	0.072	0.492	0.986
3	0.958	0.945	0.041	0.820	1.001
4	0.942	0.938	0.038	0.793	1.001
5	0.964	0.962	0.033	0.805	1.004
6	0.968	0.964	0.034	0.806	1.012
7	0.960	0.930	0.245	-1.000	1.002
8	0.510	0.483	0.224	-1.000	0.841
9	0.029	0.053	0.222	-1.000	0.535
10	0.595	0.569	0.221	-1.000	0.792
11	0.818	0.759	0.268	-1.000	0.996
standard deviation z (g)					
1	0.007	0.011	0.009	0.004	0.052
2	0.116	0.134	0.074	0.059	0.526
3	0.014	0.017	0.011	0.005	0.084
4	0.121	0.127	0.035	0.065	0.254
5	0.017	0.020	0.013	0.005	0.078
6	0.211	0.217	0.039	0.110	0.288
7	0.019	0.006	0.127	-1.000	0.082
8	0.435	0.411	0.196	-1.000	0.643
9	0.016	0.008	0.130	-1.000	0.143
10	0.408	0.388	0.194	-1.000	0.630
11	0.248	0.251	0.233	-1.000	0.721

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 2D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 4 of 6.

mvt	median	mean	s.d.	min	max
max z (g)					
1	1.020	1.037	0.087	0.891	1.516
2	1.308	1.355	0.243	1.016	2.570
3	1.014	1.022	0.067	0.861	1.193
4	1.215	1.234	0.109	1.028	1.630
5	1.041	1.069	0.099	0.917	1.492
6	1.573	1.593	0.180	1.196	2.522
7	1.042	1.026	0.263	-1.000	1.307
8	1.256	1.277	0.356	-1.000	2.383
9	0.130	0.144	0.242	-1.000	0.586
10	1.416	1.398	0.375	-1.000	2.081
11	1.313	1.404	0.456	-1.000	2.681
min z (g)					
1	0.905	0.875	0.094	0.602	0.992
2	0.642	0.581	0.315	-1.291	0.833
3	0.888	0.860	0.089	0.529	0.968
4	0.617	0.615	0.114	0.221	0.855
5	0.877	0.860	0.074	0.542	0.960
6	0.427	0.428	0.119	-0.044	0.660
7	0.864	0.817	0.243	-1.000	0.968
8	-0.339	-0.413	0.275	-1.160	-0.007
9	-0.065	-0.034	0.236	-1.000	0.479
10	-0.185	-0.221	0.197	-1.000	0.078
11	-0.092	-0.117	0.690	-1.698	0.927
range z (g)					
1	0.112	0.162	0.151	0.027	0.812
2	0.691	0.774	0.510	0.316	3.861
3	0.133	0.161	0.106	0.033	0.664
4	0.587	0.618	0.191	0.296	1.351
5	0.172	0.209	0.147	0.032	0.816
6	1.151	1.165	0.276	0.692	2.566

mvt	median	mean	s.d.	min	max
range z (g)					
7	0.200	0.193	0.189	-1.000	0.636
8	1.666	1.674	0.494	-1.000	2.918
9	0.132	0.162	0.214	-1.000	0.807
10	1.577	1.604	0.454	-1.000	2.383
11	1.450	1.505	0.921	-1.000	3.688
median r (g)					
1	1.000	0.991	0.022	0.908	1.015
2	0.999	0.992	0.021	0.909	1.020
3	1.000	0.996	0.014	0.946	1.013
4	0.998	0.992	0.020	0.915	1.031
5	1.001	0.992	0.020	0.918	1.011
6	1.001	0.995	0.030	0.897	1.047
7	1.000	0.959	0.248	-1.000	1.010
8	0.992	0.947	0.248	-1.000	1.021
9	1.002	0.945	0.251	-1.000	1.028
10	0.998	0.952	0.249	-1.000	1.025
11	1.000	0.943	0.251	-1.000	1.011
mean r (g)					
1	1.000	0.991	0.022	0.906	1.015
2	1.006	0.994	0.026	0.918	1.026
3	1.000	0.996	0.014	0.949	1.013
4	0.999	0.990	0.026	0.898	1.024
5	1.001	0.992	0.020	0.914	1.010
6	1.017	1.008	0.030	0.904	1.052
7	1.000	0.959	0.248	-1.000	1.010
8	0.992	0.951	0.249	-1.000	1.027
9	1.002	0.945	0.251	-1.000	1.028
10	0.996	0.957	0.249	-1.000	1.040
11	0.979	0.929	0.252	-1.000	1.031

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 2D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 5 of 6.

mvt	median	mean	s.d.	min	max
standard deviation r (g)					
1	0.006	0.010	0.008	0.004	0.052
2	0.111	0.120	0.046	0.057	0.249
3	0.012	0.014	0.007	0.005	0.044
4	0.121	0.126	0.035	0.058	0.264
5	0.017	0.019	0.013	0.005	0.079
6	0.224	0.225	0.041	0.103	0.294
7	0.017	0.004	0.127	-1.000	0.072
8	0.138	0.128	0.147	-1.000	0.267
9	0.008	-0.005	0.125	-1.000	0.039
10	0.140	0.138	0.152	-1.000	0.301
11	0.116	0.093	0.149	-1.000	0.246
max r (g)					
1	1.038	1.072	0.089	0.953	1.518
2	1.370	1.414	0.239	1.122	2.603
3	1.055	1.069	0.057	0.990	1.333
4	1.268	1.293	0.121	1.104	1.816
5	1.084	1.101	0.096	0.985	1.512
6	1.654	1.686	0.187	1.334	2.545
7	1.083	1.054	0.266	-1.000	1.310
8	1.664	1.650	0.449	-1.000	2.438
9	1.032	0.989	0.258	-1.000	1.175
10	1.547	1.573	0.419	-1.000	2.616
11	1.557	1.679	0.684	-1.000	3.859
min r (g)					
1	0.941	0.913	0.088	0.627	0.993
2	0.705	0.675	0.133	0.096	0.857
3	0.942	0.922	0.056	0.726	0.991
4	0.660	0.667	0.100	0.285	0.870
5	0.909	0.892	0.075	0.547	0.989
6	0.471	0.460	0.120	0.094	0.732

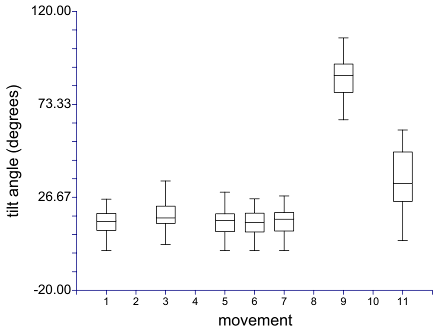
mvt	median	mean	s.d.	min	max
min r (g)					
7	0.909	0.851	0.249	-1.000	0.988
8	0.558	0.526	0.224	-1.000	0.797
9	0.960	0.903	0.248	-1.000	1.007
10	0.491	0.458	0.260	-1.000	0.845
11	0.489	0.473	0.291	-1.000	0.932
range r (g)					
1	0.111	0.160	0.154	0.026	0.810
2	0.695	0.739	0.350	0.315	2.507
3	0.114	0.147	0.094	0.032	0.583
4	0.594	0.626	0.197	0.270	1.416
5	0.181	0.209	0.150	0.027	0.854
6	1.196	1.226	0.282	0.689	2.450
7	0.183	0.188	0.190	-1.000	0.628
8	1.091	1.109	0.441	-1.000	2.017
9	0.065	0.071	0.149	-1.000	0.339
10	1.025	1.099	0.476	-1.000	2.406
11	1.145	1.191	0.758	-1.000	3.355
step rate (samples)					
med (2)	37.00	52.05	57.59	22.00	359.00
med (3)	25.50	30.02	9.97	18.00	56.50
mn(1)	24.31	24.99	4.86	17.36	47.65
mn (2)	42.70	59.32	57.77	30.84	359.00
mn (3)	34.29	37.06	9.59	24.32	74.50
sd (2)	20.94	26.64	20.51	0.00	108.78
sd (3)	19.49	21.33	9.88	10.80	69.39

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 2D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 6 of 6.

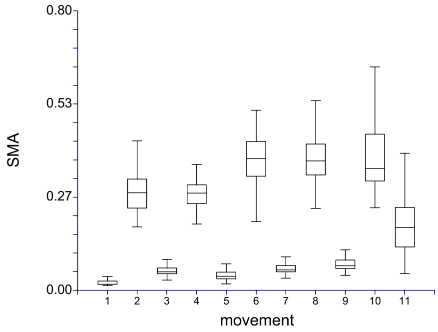
	median	mean	s.d.	min	max
frequency (Hz)					
x-axis	0.24	0.28	0.14	0.20	0.94
y-axis	0.23	0.26	0.12	0.00	0.84
z-axis	0.22	0.28	0.24	0.00	1.31
signal-to-noise ratio					
x-axis	54	57	25	17	141
y-axis	50	55	25	0	144
z-axis	19	20	15	0	93
interquartile range					
x-axis	0.010	0.019	0.022	0.004	0.144
y-axis	0.011	0.017	0.020	0.003	0.141
z-axis	0.006	0.009	0.007	0.005	0.058
magnitude	0.006	0.008	0.004	0.005	0.030

Parameters of postural sway measured during 30 s of quiet standing: sway frequency, magnitude of frequency peak and interquartile range

of sway acceleration. Overall median, mean, standard deviation, min and max are given across all repetitions of the routine by all subjects in study 2D.



(a)



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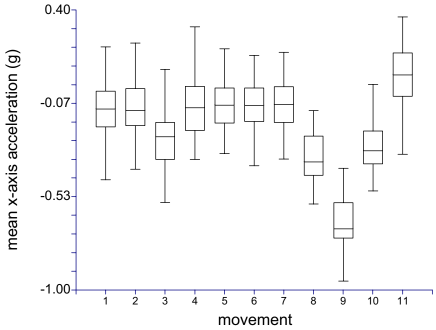

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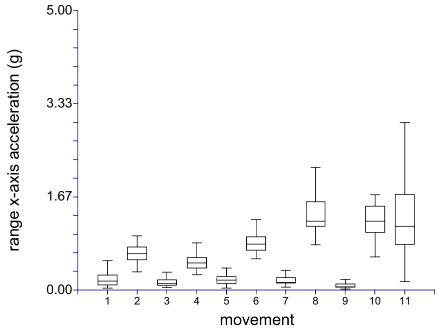

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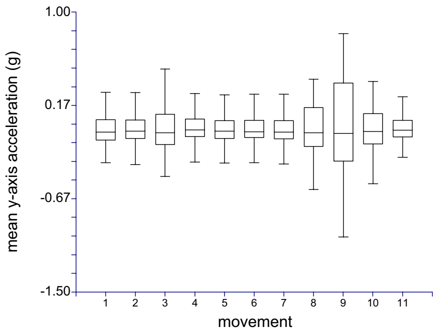

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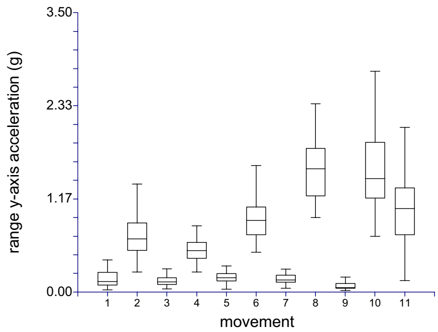
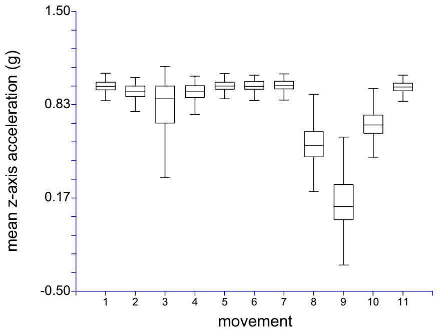
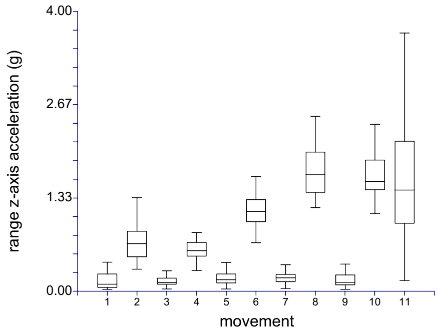


(f)

Boxplots comparing mean values for each activity across all repetitions for all subjects ($N = 11$) by movement in study 2D: (a) tilt angle; (b) SMA; (c) mean x-axis acceleration; (d) x-axis range; (e) mean y-axis acceleration; (f) y-axis range. Movements are 1: stand, 2: stand-to-sit, 3: sit, 4: sit-to-stand, 5: stand, 6: walk, 7: stand, 8: stand-to-lie, 9: lie, 10: lie-to-stand, 11: stand. Page 1 of 2.



(g)



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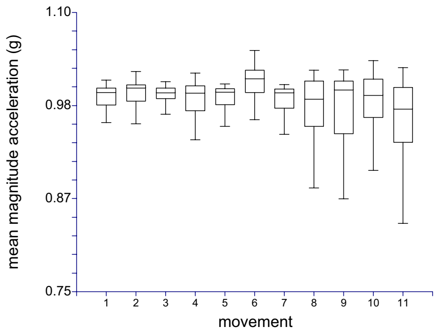
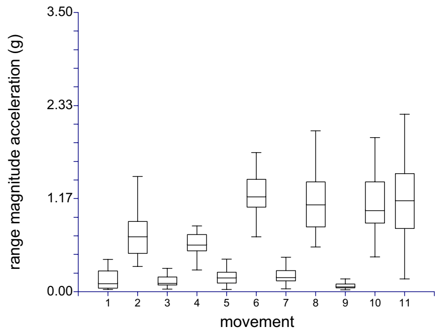
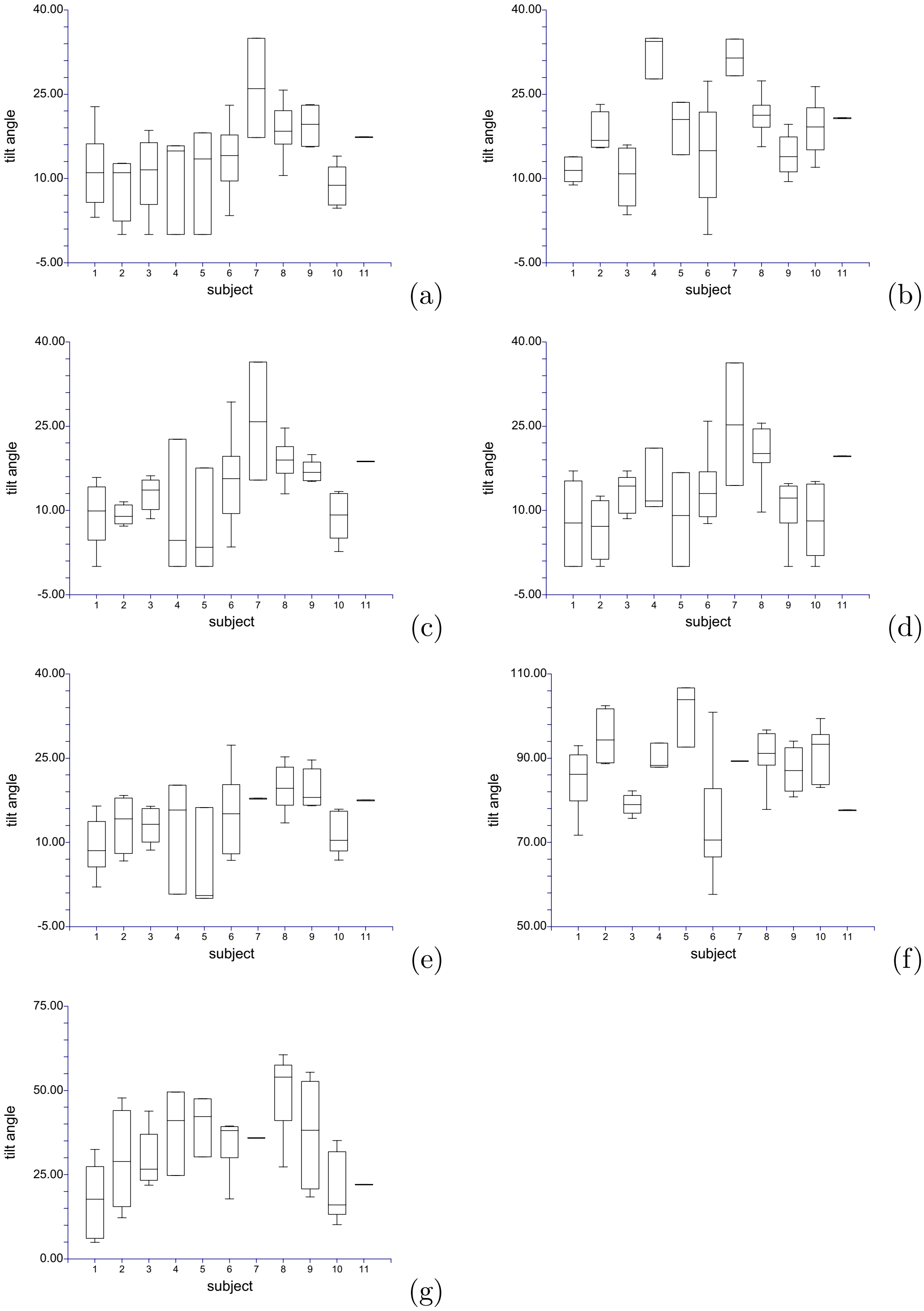


(i)

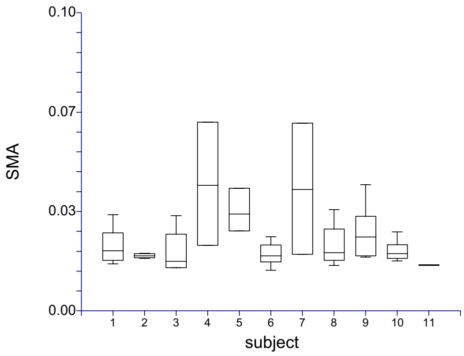


(j)

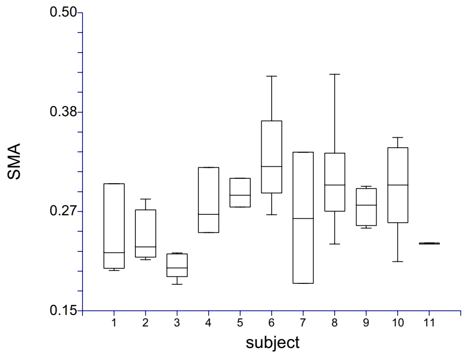
Boxplots comparing mean values for each activity across all repetitions for all subjects ($N = 11$) by movement in study 2D: (g) mean z-axis acceleration; (h) z-axis range; (i) mean magnitude acceleration, ρ; (j) magnitude acceleration, ρ, range. Movements are 1: stand, 2: stand-to-sit, 3: sit, 4: sit-to-stand, 5: stand, 6: walk, 7: stand, 8: stand-to-lie, 9: lie, 10: lie-to-stand, 11: stand. Page 2 of 2.



Boxplots of mean tilt angle for each subject in study 2D ($N = 11$) for each of the movements in the daily routine. Movements are (a) stand; (b) stand-to-sit; (c) sit; (d) sit-to-stand; (e) stand; (f) walk; (g) stand; (h) stand-to-lie; (i) lie; (j) lie-to-stand; and (k) stand. Note the different vertical axis scales between the graphs.



(a)



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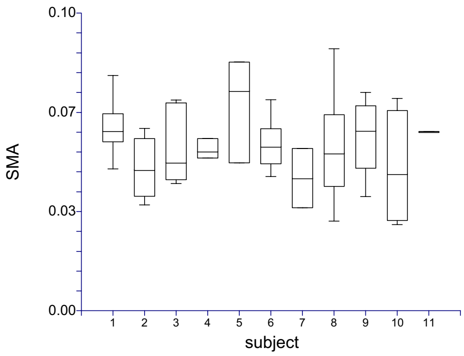

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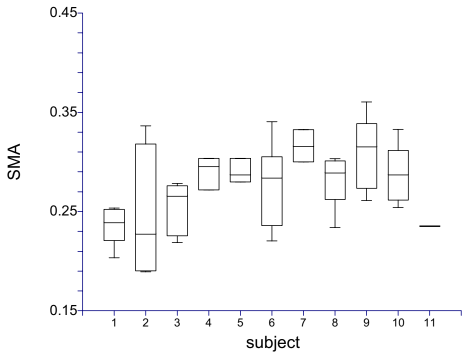

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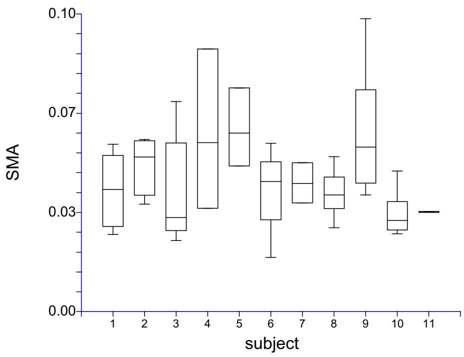

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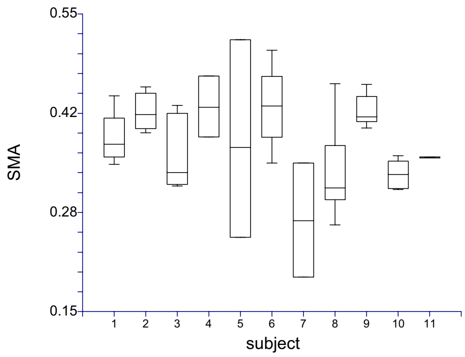
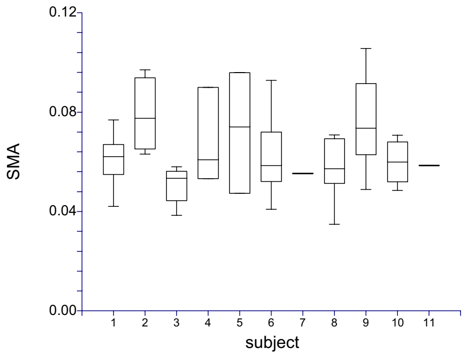
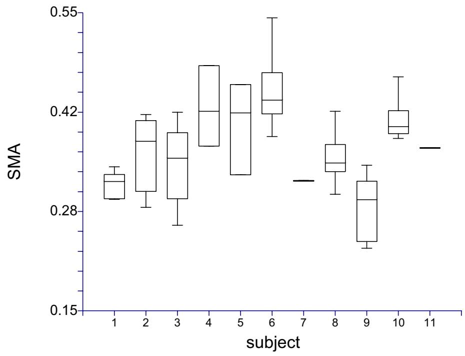


(f)

Boxplots of mean SMA for each subject in study 2D ($N = 11$) for each of the movements in the daily routine. Movements are: (a) stand; (b) stand-to-sit; (c) sit; (d) sit-to-stand; (e) stand; (f) walk. Note the different vertical axis scales between the graphs.



(g)



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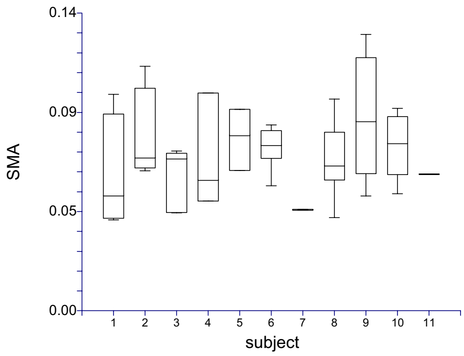
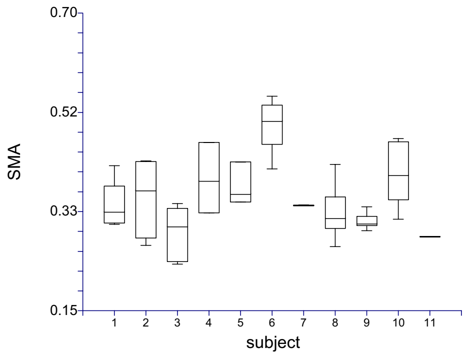
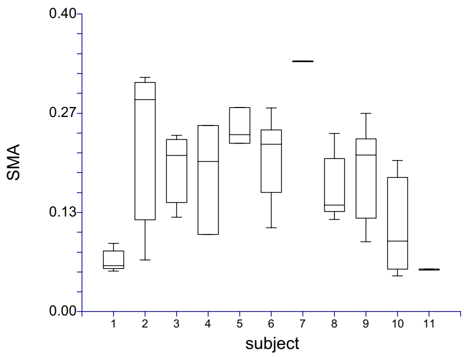


(i)



(j)



(k)

Boxplots of mean SMA for each subject ($N = 11$) in study 2D for each of the movements in the daily routine. Movements are: (g) stand; (h) stand-to-lie; (i) lie; (j) lie-to-stand; and (k) stand. Note the different vertical axis scales between the graphs.

Appendix E

Parametric Data from Study 3D

mvt	median	mean	s.d.	min	max	mvt	median	mean	s.d.	min	max
sway						duration (s)					
1	0	0	0	0	0	8	5.007	5.720	2.717	3.805	25.437
tilt (deg)						9	6.810	7.237	2.285	2.804	13.019
1	23.072	22.691	4.019	10.952	30.271	10	5.008	5.452	0.839	4.006	9.013
3	29.897	29.747	6.551	12.848	42.514	11	15.823	15.813	2.189	1.803	21.030
5	23.259	22.418	4.106	12.102	29.966	SMA (g)					
6	19.979	19.585	3.680	10.427	24.590	1	0.025	0.026	0.005	0.017	0.036
7	21.146	20.550	4.122	11.988	29.025	2	0.334	0.345	0.073	0.233	0.788
9	88.179	86.865	5.479	71.270	96.626	3	0.064	0.065	0.014	0.039	0.108
11	21.726	21.510	4.509	11.788	29.686	4	0.325	0.334	0.048	0.238	0.445
duration (s)						5	0.050	0.052	0.011	0.035	0.101
1	28.641	28.965	1.102	27.640	33.829	6	0.426	0.433	0.058	0.300	0.609
2	3.005	3.379	0.666	1.001	5.027	7	0.075	0.074	0.013	0.053	0.125
3	8.813	9.999	4.640	6.008	36.652	8	0.390	0.388	0.031	0.300	0.468
4	3.004	3.904	4.969	1.803	41.659	9	0.073	0.075	0.013	0.051	0.107
5	7.821	8.094	1.861	5.819	14.030	10	0.358	0.360	0.030	0.292	0.441
6	21.431	21.201	2.701	6.219	26.438	11	0.039	0.050	0.037	0.030	0.246
7	7.010	7.020	1.540	2.003	11.015						

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 3D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 1 of 6.

mvt	median	mean	s.d.	min	max
median x (g)					
1	-0.341	-0.327	0.077	-0.468	0.077
2	-0.283	-0.276	0.088	-0.416	0.088
3	-0.433	-0.431	0.101	-0.613	0.101
4	-0.279	-0.258	0.097	-0.410	0.097
5	-0.326	-0.317	0.083	-0.471	0.083
6	-0.253	-0.249	0.074	-0.368	0.074
7	-0.289	-0.280	0.078	-0.441	0.078
8	-0.354	-0.365	0.118	-0.753	0.118
9	-0.721	-0.699	0.129	-0.937	0.129
10	-0.336	-0.343	0.122	-0.608	0.122
11	-0.307	-0.298	0.084	-0.465	0.084
mean x (g)					
1	-0.337	-0.324	0.077	-0.466	0.077
2	-0.184	-0.184	0.085	-0.375	0.085
3	-0.434	-0.430	0.102	-0.606	0.102
4	-0.183	-0.180	0.090	-0.350	0.090
5	-0.325	-0.312	0.082	-0.464	0.082
6	-0.267	-0.259	0.076	-0.381	0.076
7	-0.286	-0.276	0.077	-0.435	0.077
8	-0.410	-0.397	0.077	-0.577	0.077
9	-0.724	-0.701	0.127	-0.938	0.127
10	-0.395	-0.367	0.094	-0.503	0.094
11	-0.300	-0.293	0.082	-0.462	0.082
standard deviation x (g)					
1	0.017	0.019	0.008	0.006	0.043
2	0.221	0.231	0.046	0.151	0.383
3	0.020	0.022	0.011	0.009	0.058
4	0.213	0.233	0.057	0.138	0.395
5	0.022	0.025	0.011	0.011	0.077
6	0.165	0.169	0.021	0.122	0.232

mvt	median	mean	s.d.	min	max
standard deviation x (g)					
7	0.023	0.027	0.012	0.012	0.065
8	0.305	0.292	0.057	0.134	0.386
9	0.016	0.017	0.007	0.007	0.045
10	0.330	0.317	0.064	0.158	0.469
11	0.023	0.032	0.038	0.009	0.280
max x (g)					
1	-0.270	-0.261	0.078	-0.425	0.078
2	0.317	0.334	0.128	0.081	0.612
3	-0.361	-0.357	0.107	-0.543	0.107
4	0.279	0.323	0.211	-0.068	1.262
5	-0.231	-0.229	0.094	-0.365	0.094
6	0.175	0.194	0.132	-0.043	0.665
7	-0.213	-0.182	0.102	-0.322	0.102
8	0.272	0.261	0.139	-0.074	0.606
9	-0.670	-0.643	0.139	-0.872	0.139
10	0.354	0.348	0.151	0.035	0.846
11	-0.218	-0.178	0.163	-0.343	0.714
min x (g)					
1	-0.377	-0.364	0.079	-0.510	0.079
2	-0.452	-0.454	0.126	-1.071	0.126
3	-0.482	-0.488	0.110	-0.769	0.110
4	-0.456	-0.462	0.119	-0.867	0.119
5	-0.395	-0.382	0.085	-0.553	0.085
6	-0.772	-0.772	0.108	-0.953	0.108
7	-0.344	-0.335	0.078	-0.565	0.078
8	-0.880	-0.886	0.147	-1.200	0.147
9	-0.773	-0.762	0.122	-0.990	0.122
10	-0.798	-0.784	0.117	-1.073	0.117
11	-0.356	-0.356	0.123	-0.873	0.123

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 3D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 2 of 6.

mvt	median	mean	s.d.	min	max	mvt	median	mean	s.d.	min	max
range x (g)						mean y (g)					
1	0.096	0.102	0.039	0.039	0.191	7	0.061	0.064	0.109	-0.209	0.288
2	0.782	0.788	0.155	0.523	1.174	8	-0.341	-0.333	0.097	-0.598	0.097
3	0.112	0.131	0.068	0.048	0.386	9	-0.676	-0.677	0.125	-0.927	0.125
4	0.732	0.785	0.259	0.467	2.129	10	-0.310	-0.316	0.083	-0.525	0.083
5	0.137	0.152	0.071	0.067	0.512	11	0.063	0.066	0.101	-0.142	0.264
6	0.942	0.966	0.135	0.688	1.397	standard deviation y (g)					
7	0.134	0.154	0.072	0.054	0.372	1	0.010	0.011	0.004	0.005	0.029
8	1.146	1.146	0.209	0.572	1.590	2	0.230	0.235	0.047	0.150	0.357
9	0.111	0.120	0.056	0.036	0.277	3	0.014	0.016	0.011	0.007	0.085
10	1.168	1.131	0.202	0.609	1.682	4	0.217	0.221	0.038	0.143	0.294
11	0.115	0.178	0.225	0.039	1.587	5	0.023	0.024	0.009	0.011	0.066
median y (g)						6	0.183	0.188	0.031	0.129	0.256
1	0.040	0.032	0.103	-0.244	0.212	7	0.023	0.024	0.007	0.011	0.040
2	0.057	0.051	0.107	-0.244	0.277	8	0.439	0.428	0.061	0.261	0.541
3	-0.154	-0.147	0.122	-0.399	0.122	9	0.016	0.017	0.007	0.006	0.038
4	0.072	0.071	0.107	-0.167	0.320	10	0.425	0.421	0.062	0.274	0.565
5	0.041	0.045	0.113	-0.206	0.258	11	0.017	0.028	0.035	0.007	0.251
6	0.023	0.028	0.098	-0.190	0.218	max y (g)					
7	0.063	0.062	0.109	-0.206	0.286	1	0.075	0.078	0.102	-0.123	0.304
8	-0.500	-0.452	0.226	-0.818	0.242	2	0.683	0.683	0.168	0.301	1.023
9	-0.678	-0.680	0.126	-0.931	0.126	3	-0.107	-0.088	0.122	-0.322	0.221
10	-0.506	-0.481	0.192	-0.838	0.192	4	0.616	0.642	0.171	0.252	1.042
11	0.062	0.065	0.101	-0.145	0.264	5	0.131	0.138	0.122	-0.095	0.370
mean y (g)						6	0.686	0.737	0.226	0.351	1.463
1	0.038	0.032	0.103	-0.243	0.212	7	0.146	0.144	0.116	-0.139	0.335
2	0.116	0.115	0.107	-0.198	0.365	8	0.440	0.438	0.133	0.106	0.865
3	-0.157	-0.146	0.122	-0.397	0.123	9	-0.636	-0.618	0.126	-0.875	0.126
4	0.107	0.110	0.105	-0.161	0.311	10	0.406	0.413	0.139	0.103	0.863
5	0.047	0.048	0.111	-0.189	0.259	11	0.134	0.163	0.149	-0.086	0.765
6	0.042	0.050	0.107	-0.188	0.246						

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 3D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 3 of 6.

mvt	median	mean	s.d.	min	max
min y (g)					
1	-0.012	-0.011	0.115	-0.327	0.187
2	-0.185	-0.188	0.155	-0.793	0.155
3	-0.216	-0.203	0.131	-0.466	0.131
4	-0.181	-0.201	0.261	-1.963	0.261
5	-0.030	-0.044	0.128	-0.340	0.184
6	-0.509	-0.503	0.147	-0.950	0.147
7	-0.018	-0.015	0.117	-0.293	0.258
8	-1.133	-1.124	0.158	-1.848	0.158
9	-0.727	-0.722	0.121	-0.966	0.121
10	-1.020	-1.020	0.141	-1.407	0.141
11	0.011	-0.021	0.189	-0.853	0.218
range y (g)					
1	0.070	0.088	0.054	0.040	0.335
2	0.867	0.870	0.169	0.552	1.227
3	0.099	0.115	0.078	0.037	0.559
4	0.773	0.843	0.293	0.511	2.748
5	0.164	0.182	0.088	0.064	0.483
6	1.194	1.240	0.267	0.782	2.204
7	0.154	0.159	0.060	0.052	0.315
8	1.555	1.561	0.202	0.978	2.183
9	0.101	0.104	0.045	0.031	0.273
10	1.427	1.434	0.207	0.908	1.946
11	0.104	0.184	0.271	0.043	1.458
median z (g)					
1	0.920	0.920	0.026	0.861	0.981
2	0.903	0.899	0.036	0.722	0.965
3	0.870	0.862	0.057	0.725	0.976
4	0.907	0.905	0.028	0.850	0.970
5	0.915	0.921	0.027	0.861	0.976
6	0.917	0.919	0.021	0.881	0.964

mvt	median	mean	s.d.	min	max
median z (g)					
7	0.932	0.933	0.025	0.872	0.976
8	0.555	0.529	0.224	0.054	0.915
9	0.036	0.053	0.094	-0.116	0.316
10	0.678	0.644	0.166	0.094	0.960
11	0.930	0.928	0.028	0.867	0.979
mean z (g)					
1	0.920	0.920	0.026	0.864	0.982
2	0.889	0.890	0.031	0.816	0.940
3	0.867	0.863	0.056	0.737	0.975
4	0.894	0.895	0.031	0.811	0.958
5	0.919	0.922	0.026	0.866	0.978
6	0.940	0.940	0.020	0.909	0.983
7	0.933	0.934	0.025	0.874	0.978
8	0.475	0.487	0.079	0.290	0.694
9	0.032	0.054	0.095	-0.115	0.321
10	0.520	0.532	0.067	0.408	0.762
11	0.929	0.927	0.028	0.869	0.979
standard deviation z (g)					
1	0.008	0.008	0.003	0.004	0.021
2	0.094	0.102	0.057	0.054	0.502
3	0.015	0.017	0.009	0.007	0.054
4	0.084	0.090	0.028	0.049	0.215
5	0.015	0.016	0.007	0.007	0.049
6	0.213	0.218	0.043	0.139	0.449
7	0.017	0.017	0.006	0.007	0.034
8	0.459	0.451	0.050	0.307	0.520
9	0.017	0.020	0.010	0.006	0.051
10	0.428	0.424	0.047	0.300	0.522
11	0.011	0.018	0.025	0.005	0.155

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 3D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 4 of 6.

mvt	median	mean	s.d.	min	max
max z (g)					
1	0.953	0.954	0.028	0.898	1.042
2	1.187	1.222	0.222	0.955	2.513
3	0.935	0.932	0.057	0.810	1.096
4	1.158	1.158	0.116	0.956	1.663
5	0.984	0.998	0.060	0.918	1.318
6	1.633	1.636	0.138	1.377	2.125
7	1.013	1.019	0.053	0.915	1.186
8	1.330	1.347	0.145	1.036	2.010
9	0.102	0.126	0.106	-0.044	0.388
10	1.358	1.334	0.158	0.982	1.989
11	0.984	1.025	0.117	0.918	1.606
min z (g)					
1	0.894	0.895	0.029	0.806	0.961
2	0.654	0.637	0.091	0.287	0.783
3	0.802	0.789	0.085	0.540	0.907
4	0.700	0.666	0.177	-0.461	0.820
5	0.852	0.850	0.051	0.714	0.950
6	0.489	0.472	0.102	0.048	0.668
7	0.861	0.861	0.042	0.769	0.933
8	-0.234	-0.231	0.147	-0.525	0.178
9	-0.021	-0.016	0.108	-0.298	0.293
10	-0.112	-0.138	0.151	-0.756	0.189
11	0.893	0.859	0.113	0.163	0.947
range z (g)					
1	0.054	0.059	0.026	0.026	0.157
2	0.551	0.585	0.268	0.288	2.226
3	0.113	0.143	0.086	0.049	0.466
4	0.437	0.492	0.231	0.225	1.782
5	0.135	0.147	0.085	0.040	0.572
6	1.127	1.163	0.218	0.781	2.077
mvt	median	mean	s.d.	min	max
range z (g)					
7	0.144	0.158	0.077	0.040	0.417
8	1.588	1.578	0.217	1.048	2.260
9	0.124	0.142	0.075	0.029	0.332
10	1.457	1.472	0.242	0.935	2.287
11	0.091	0.166	0.218	0.043	1.423
median r (g)					
1	0.988	0.985	0.011	0.919	0.999
2	0.985	0.983	0.015	0.898	0.999
3	0.993	0.990	0.013	0.921	1.006
4	0.985	0.984	0.010	0.929	0.997
5	0.987	0.985	0.011	0.922	1.000
6	0.981	0.980	0.014	0.929	1.027
7	0.988	0.986	0.011	0.922	0.999
8	0.992	0.989	0.012	0.926	1.008
9	1.002	0.997	0.019	0.911	1.012
10	0.998	0.995	0.013	0.930	1.009
11	0.988	0.986	0.010	0.923	0.999
mean r (g)					
1	0.988	0.985	0.011	0.919	0.999
2	0.987	0.986	0.007	0.944	0.997
3	0.993	0.990	0.013	0.922	1.006
4	0.987	0.987	0.007	0.950	0.996
5	0.987	0.986	0.011	0.922	1.000
6	1.013	1.013	0.012	0.962	1.035
7	0.988	0.986	0.011	0.923	1.000
8	0.998	0.996	0.011	0.950	1.010
9	1.003	0.997	0.019	0.911	1.012
10	0.998	0.997	0.010	0.956	1.011
11	0.988	0.987	0.011	0.923	1.007

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 3D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 5 of 6.

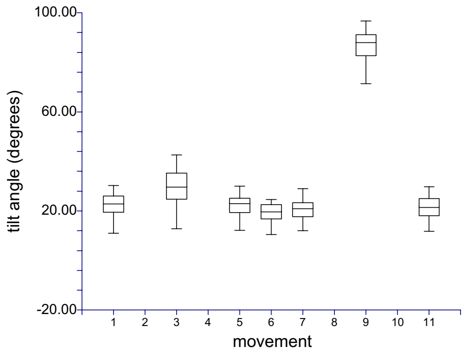
mvt	median	mean	s.d.	min	max
standard deviation r (g)					
1	0.005	0.005	0.001	0.004	0.008
2	0.081	0.092	0.059	0.043	0.514
3	0.010	0.012	0.005	0.005	0.033
4	0.081	0.086	0.022	0.030	0.146
5	0.011	0.013	0.007	0.006	0.047
6	0.225	0.237	0.046	0.148	0.462
7	0.014	0.015	0.006	0.006	0.035
8	0.108	0.116	0.034	0.054	0.251
9	0.010	0.010	0.003	0.005	0.018
10	0.094	0.096	0.022	0.046	0.167
11	0.007	0.014	0.021	0.005	0.146
max r (g)					
1	1.008	1.009	0.017	0.947	1.059
2	1.269	1.318	0.227	1.121	2.753
3	1.041	1.048	0.038	0.975	1.181
4	1.292	1.308	0.160	1.099	2.215
5	1.044	1.062	0.062	0.963	1.333
6	1.731	1.740	0.149	1.503	2.185
7	1.060	1.065	0.047	0.957	1.211
8	1.400	1.435	0.193	1.072	2.274
9	1.048	1.044	0.032	0.941	1.106
10	1.405	1.409	0.138	1.175	1.997
11	1.032	1.075	0.116	0.983	1.651
min r (g)					
1	0.968	0.963	0.015	0.901	0.984
2	0.762	0.741	0.089	0.308	0.885
3	0.932	0.922	0.041	0.766	0.977
4	0.770	0.759	0.084	0.363	0.899
5	0.918	0.916	0.039	0.772	0.979
6	0.533	0.523	0.087	0.151	0.684

mvt	median	mean	s.d.	min	max
min r (g)					
7	0.917	0.911	0.036	0.802	0.962
8	0.687	0.665	0.106	0.349	0.814
9	0.956	0.948	0.032	0.858	0.989
10	0.723	0.702	0.090	0.364	0.838
11	0.944	0.916	0.072	0.533	0.976
range r (g)					
1	0.037	0.045	0.023	0.027	0.143
2	0.509	0.577	0.293	0.236	2.445
3	0.105	0.126	0.070	0.037	0.375
4	0.511	0.549	0.233	0.199	1.718
5	0.130	0.146	0.090	0.030	0.550
6	1.179	1.217	0.220	0.829	2.034
7	0.146	0.153	0.074	0.036	0.372
8	0.714	0.770	0.264	0.445	1.799
9	0.086	0.097	0.046	0.023	0.200
10	0.693	0.707	0.203	0.336	1.633
11	0.088	0.159	0.182	0.031	1.118
step rate (samples)					
med (2)	26.00	26.42	1.77	17.50	30.00
mn(1)	1.54	1.55	0.12	1.39	2.30
mn (2)	29.63	30.18	3.37	17.40	37.65
sd (2)	9.96	10.23	4.35	1.14	20.26

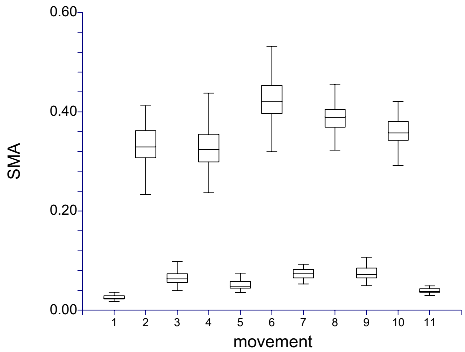
Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 3D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 6 of 6.

	median	mean	s.d.	min	max
frequency (Hz)					
x-axis	0.23	0.25	0.05	0.20	0.40
y-axis	0.22	0.22	0.02	0.20	0.27
z-axis	0.28	0.29	0.13	0.20	1.18
signal-to-noise ratio					
x-axis	85	89	24	48	170
y-axis	71	72	19	31	120
z-axis	25	29	14	10	65
interquartile range					
x-axis	0.088	0.099	0.043	0.036	0.312
y-axis	0.115	0.134	0.052	0.059	0.288
z-axis	0.062	0.074	0.043	0.018	0.205
magnitude	0.014	0.015	0.003	0.011	0.027

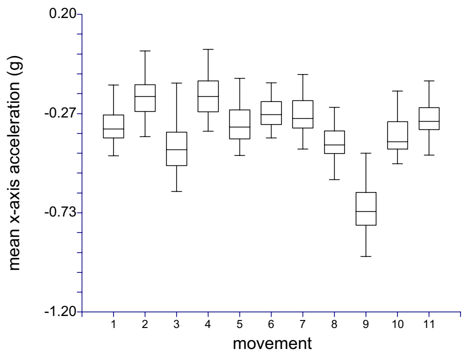
Parameters of postural sway measured during 30 s of quiet standing: sway frequency, magnitude of frequency peak and interquartile range of sway acceleration. Overall median, mean, standard deviation, min and max are given across all repetitions of the routine in study 3D.



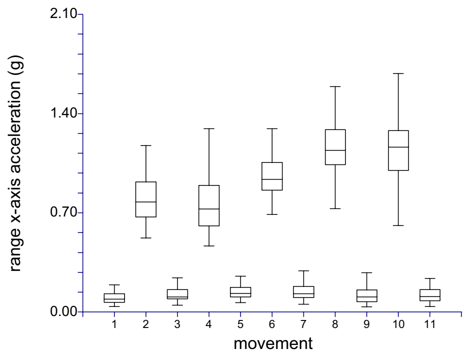
(a)



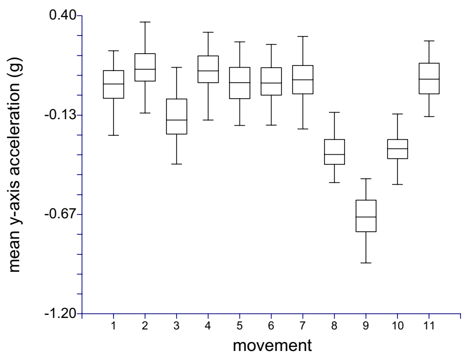
(b)



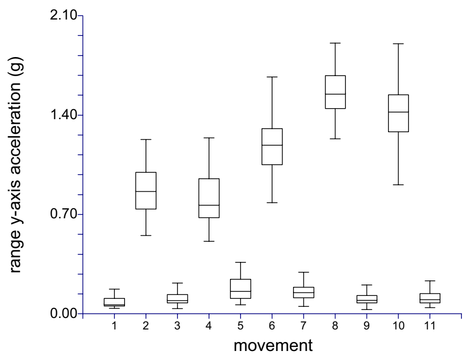
(c)



(d)

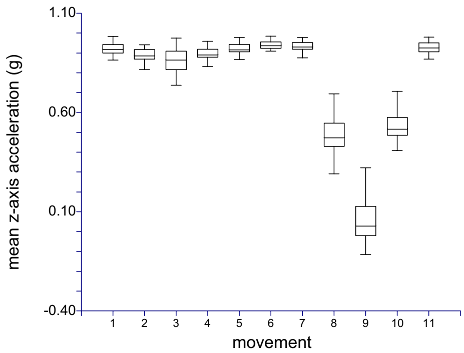


(e)

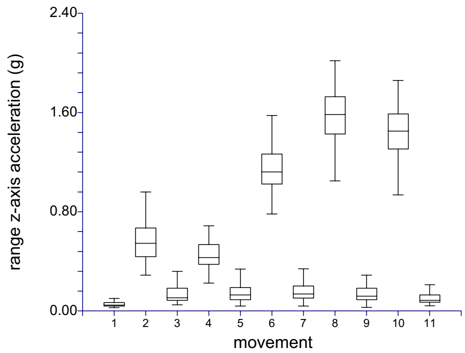


(f)

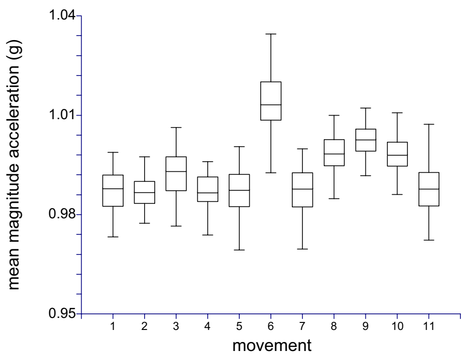
Boxplots comparing mean values for each activity across all repetitions by movement in study 3D: (a) tilt angle; (b) SMA; (c) mean x-axis acceleration; (d) x-axis range; (e) mean y-axis acceleration; (f) y-axis range. Movements are 1: stand, 2: stand-to-sit, 3: sit, 4: sit-to-stand, 5: stand, 6: walk, 7: stand, 8: stand-to-lie, 9: lie, 10: lie-to-stand, 11: stand Page 1 of 2.



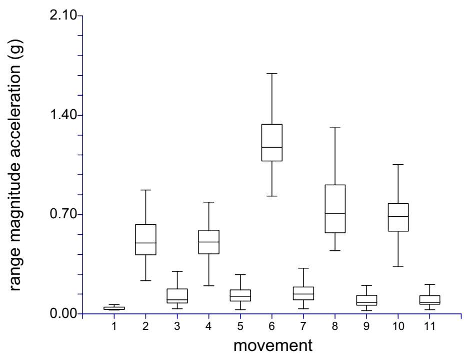
(g)



(h)



(i)



(j)

Boxplots comparing mean values for each activity across all repetitions by movement in study 3D: (g) mean z-axis acceleration; (h) z-axis range; (i) mean magnitude acceleration, ρ; (j) magnitude acceleration, ρ, range. Movements are 1: stand, 2: stand-to-sit, 3: sit, 4: sit-to-stand, 5: stand, 6: walk, 7: stand, 8: stand-to-lie, 9: lie, 10: lie-to-stand, 11: stand Page 2 of 2.

Appendix F

Parametric Data from Study 4D

mvt	median	mean	s.d.	min	max
sway					
1	0	0	0	0	0
tilt (deg)					
1	14.267	13.508	9.729	0.000	64.142
3	28.214	29.363	19.513	0.000	87.779
5	13.526	13.042	9.513	0.000	61.860
6	14.669	12.835	9.278	0.000	59.797
7	13.082	12.351	9.446	0.000	62.964
9	83.859	82.563	12.998	6.491	111.908
11	15.349	16.248	11.488	0.000	62.602
duration (s)					
1	28.865	27.982	4.259	1.858	67.780
2	4.280	4.781	2.344	0.896	16.260
3	15.550	15.706	3.212	1.597	30.650
4	3.190	3.496	1.348	0.726	14.550
5	18.070	18.646	4.332	2.582	41.140
6	61.350	62.936	11.391	3.126	137.480
7	14.170	15.252	7.546	3.255	96.560

mvt	median	mean	s.d.	min	max
duration (s)					
8	6.040	6.418	1.723	0.904	13.510
9	14.940	14.696	2.824	1.302	22.960
10	5.740	5.996	1.483	0.863	25.930
11	23.180	23.055	3.208	1.573	38.340
SMA (g)					
1	0.025	0.028	0.013	0.007	0.211
2	0.279	0.284	0.052	0.024	0.484
3	0.054	0.058	0.020	0.010	0.169
4	0.258	0.257	0.054	0.022	0.456
5	0.040	0.044	0.018	0.008	0.215
6	0.277	0.282	0.043	0.015	0.428
7	0.056	0.061	0.024	0.012	0.360
8	0.326	0.323	0.062	0.034	0.530
9	0.065	0.066	0.012	0.009	0.143
10	0.259	0.262	0.050	0.026	0.504
11	0.082	0.089	0.038	0.020	0.285

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 4D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 1 of 6.

mvt	median	mean	s.d.	min	max
median x (g)					
1	-0.188	-0.131	0.210	-0.777	0.521
2	-0.156	-0.132	0.207	-0.835	0.584
3	-0.310	-0.370	0.272	-0.978	0.758
4	-0.172	-0.150	0.226	-0.838	0.514
5	-0.187	-0.135	0.206	-0.728	0.424
6	-0.159	-0.094	0.194	-0.639	0.430
7	-0.183	-0.126	0.201	-0.741	0.499
8	-0.327	-0.381	0.277	-0.952	0.728
9	-0.824	-0.661	0.379	-1.213	0.983
10	-0.295	-0.308	0.252	-0.962	0.687
11	-0.172	-0.115	0.207	-0.756	0.461
mean x (g)					
1	-0.187	-0.129	0.209	-0.772	0.544
2	-0.169	-0.144	0.188	-0.631	0.573
3	-0.303	-0.365	0.265	-0.975	0.741
4	-0.179	-0.158	0.208	-0.664	0.414
5	-0.184	-0.132	0.205	-0.725	0.426
6	-0.153	-0.091	0.194	-0.630	0.431
7	-0.175	-0.122	0.197	-0.740	0.503
8	-0.338	-0.347	0.172	-0.801	0.571
9	-0.823	-0.661	0.376	-1.210	0.978
10	-0.305	-0.317	0.182	-0.715	0.478
11	-0.179	-0.124	0.206	-0.745	0.439
standard deviation x (g)					
1	0.018	0.024	0.026	0.005	0.427
2	0.176	0.195	0.095	0.032	0.463
3	0.034	0.044	0.031	0.009	0.286
4	0.186	0.191	0.092	0.034	0.446
5	0.032	0.036	0.021	0.009	0.255
6	0.106	0.119	0.039	0.008	0.442

mvt	median	mean	s.d.	min	max
standard deviation x (g)					
7	0.033	0.041	0.036	0.010	0.499
8	0.371	0.340	0.169	0.052	0.734
9	0.024	0.027	0.013	0.007	0.116
10	0.301	0.303	0.149	0.047	0.660
11	0.062	0.104	0.119	0.014	0.703
max x (g)					
1	-0.069	-0.022	0.224	-0.503	0.898
2	0.186	0.223	0.249	-0.248	1.049
3	-0.193	-0.209	0.258	-0.929	0.846
4	0.094	0.173	0.270	-0.240	1.116
5	-0.051	0.018	0.237	-0.488	1.503
6	0.202	0.297	0.299	-0.324	1.379
7	-0.032	0.037	0.231	-0.497	1.266
8	0.204	0.230	0.244	-0.239	1.423
9	-0.676	-0.549	0.376	-1.093	1.099
10	0.112	0.205	0.276	-0.299	1.246
11	0.097	0.196	0.282	-0.396	1.482
min x (g)					
1	-0.246	-0.205	0.215	-1.383	0.393
2	-0.543	-0.562	0.294	-1.498	0.396
3	-0.405	-0.489	0.272	-1.298	0.555
4	-0.445	-0.474	0.253	-1.498	0.309
5	-0.280	-0.262	0.211	-0.915	0.347
6	-0.448	-0.433	0.173	-1.109	0.212
7	-0.275	-0.243	0.219	-1.563	0.418
8	-1.029	-0.920	0.311	-1.530	0.311
9	-0.927	-0.766	0.370	-1.341	0.927
10	-0.889	-0.797	0.268	-1.288	0.268
11	-0.396	-0.468	0.736	-13.207	1.665

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 4D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 2 of 6.

mvt	median	mean	s.d.	min	max
range x (g)					
1	0.163	0.183	0.134	0.028	1.541
2	0.736	0.785	0.325	0.143	1.951
3	0.238	0.280	0.169	0.062	1.417
4	0.605	0.647	0.288	0.098	2.066
5	0.254	0.281	0.174	0.054	2.154
6	0.643	0.730	0.261	0.099	2.207
7	0.234	0.279	0.202	0.051	2.829
8	1.279	1.150	0.459	0.166	2.223
9	0.191	0.217	0.132	0.036	1.595
10	1.012	1.002	0.429	0.157	2.422
11	0.469	0.664	0.804	0.097	13.434
median y (g)					
1	-0.068	-0.046	0.145	-0.369	0.441
2	-0.062	-0.033	0.163	-0.427	0.619
3	-0.080	-0.043	0.191	-0.463	0.488
4	-0.042	-0.024	0.157	-0.473	0.463
5	-0.066	-0.049	0.139	-0.415	0.388
6	-0.063	-0.032	0.146	-0.388	0.404
7	-0.069	-0.048	0.131	-0.441	0.378
8	-0.063	-0.072	0.312	-0.954	0.657
9	-0.088	-0.080	0.497	-1.008	0.806
10	-0.053	-0.051	0.230	-0.823	0.582
11	-0.060	-0.046	0.132	-0.496	0.443
mean y (g)					
1	-0.067	-0.046	0.145	-0.346	0.439
2	-0.061	-0.039	0.150	-0.410	0.622
3	-0.075	-0.040	0.188	-0.467	0.492
4	-0.047	-0.028	0.148	-0.501	0.492
5	-0.060	-0.047	0.137	-0.438	0.376
6	-0.063	-0.031	0.148	-0.387	0.414
mean y (g)					
7	-0.066	-0.047	0.131	-0.443	0.376
8	-0.075	-0.059	0.225	-0.584	0.400
9	-0.094	-0.078	0.499	-1.008	0.808
10	-0.061	-0.056	0.189	-0.533	0.380
11	-0.050	-0.036	0.129	-0.494	0.447
standard deviation y (g)					
1	0.017	0.020	0.021	0.005	0.244
2	0.151	0.155	0.054	0.027	0.357
3	0.028	0.033	0.020	0.008	0.168
4	0.131	0.136	0.050	0.031	0.354
5	0.027	0.031	0.017	0.008	0.170
6	0.109	0.113	0.030	0.013	0.499
7	0.028	0.033	0.024	0.008	0.328
8	0.289	0.303	0.149	0.039	0.645
9	0.026	0.028	0.014	0.006	0.082
10	0.298	0.294	0.137	0.038	0.597
11	0.063	0.076	0.049	0.010	0.516
max y (g)					
1	0.036	0.050	0.150	-0.295	0.572
2	0.251	0.276	0.190	-0.264	0.989
3	0.040	0.074	0.205	-0.427	1.259
4	0.191	0.218	0.193	-0.267	0.817
5	0.059	0.086	0.154	-0.373	0.714
6	0.270	0.320	0.198	-0.062	1.235
7	0.059	0.085	0.171	-0.391	1.246
8	0.538	0.509	0.291	-0.052	1.733
9	-0.001	0.039	0.524	-0.969	1.078
10	0.446	0.493	0.301	-0.063	1.287
11	0.186	0.227	0.205	-0.324	1.276

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 4D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 3 of 6.

mvt	median	mean	s.d.	min	max
min y (g)					
1	-0.139	-0.126	0.158	-0.812	0.322
2	-0.365	-0.365	0.175	-0.909	0.387
3	-0.161	-0.141	0.181	-0.709	0.378
4	-0.267	-0.285	0.182	-0.928	0.293
5	-0.158	-0.160	0.156	-1.058	0.283
6	-0.366	-0.417	0.638	-12.407	1.481
7	-0.169	-0.167	0.163	-1.185	0.241
8	-0.496	-0.581	0.301	-1.501	0.352
9	-0.214	-0.166	0.490	-1.138	0.715
10	-0.483	-0.555	0.262	-1.511	0.262
11	-0.278	-0.321	0.698	-13.645	1.728
range y (g)					
1	0.160	0.176	0.111	0.026	1.253
2	0.644	0.640	0.191	0.108	1.868
3	0.183	0.215	0.130	0.057	1.791
4	0.497	0.503	0.173	0.099	1.096
5	0.224	0.246	0.125	0.048	1.554
6	0.658	0.737	0.643	0.093	13.081
7	0.215	0.252	0.165	0.050	1.977
8	1.089	1.092	0.407	0.166	2.379
9	0.188	0.205	0.101	0.037	0.813
10	1.111	1.048	0.391	0.160	1.881
11	0.479	0.548	0.709	0.094	13.925
median z (g)					
1	0.970	0.966	0.099	0.026	1.261
2	0.936	0.928	0.102	0.026	1.219
3	0.878	0.819	0.198	0.035	1.105
4	0.937	0.930	0.101	0.027	1.164
5	0.972	0.968	0.098	0.020	1.293
6	0.959	0.957	0.095	0.027	1.287
median z (g)					
7	0.973	0.971	0.099	0.020	1.284
8	0.652	0.606	0.250	-0.136	1.027
9	0.102	0.120	0.189	-0.379	0.927
10	0.814	0.797	0.131	0.077	1.001
11	0.974	0.969	0.098	0.017	1.299
mean z (g)					
1	0.969	0.965	0.099	0.025	1.264
2	0.930	0.922	0.104	0.030	1.224
3	0.881	0.825	0.189	0.039	1.105
4	0.931	0.918	0.105	0.028	1.186
5	0.972	0.969	0.098	0.019	1.295
6	0.967	0.968	0.095	0.025	1.294
7	0.974	0.971	0.099	0.023	1.289
8	0.544	0.552	0.133	0.073	0.959
9	0.107	0.126	0.187	-0.373	0.925
10	0.692	0.686	0.110	0.080	0.947
11	0.964	0.946	0.111	0.025	1.305
standard deviation z (g)					
1	0.010	0.013	0.011	0.003	0.118
2	0.133	0.140	0.042	0.021	0.333
3	0.028	0.038	0.029	0.009	0.272
4	0.101	0.114	0.047	0.015	0.398
5	0.019	0.024	0.025	0.005	0.339
6	0.150	0.152	0.037	0.016	0.646
7	0.021	0.025	0.020	0.006	0.293
8	0.416	0.413	0.080	0.058	0.621
9	0.041	0.045	0.026	0.008	0.249
10	0.325	0.319	0.085	0.064	0.637
11	0.053	0.090	0.107	0.008	0.475

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 4D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 4 of 6.

mvt	median	mean	s.d.	min	max	mvt	median	mean	s.d.	min	max
max z (g)						range z (g)					
1	1.033	1.041	0.117	0.038	1.631	7	0.214	0.262	0.183	0.031	1.654
2	1.377	1.404	0.241	0.125	2.582	8	1.434	1.462	0.276	0.149	2.275
3	1.022	0.984	0.166	0.056	1.545	9	0.278	0.304	0.186	0.042	1.809
4	1.207	1.211	0.153	0.073	1.784	10	1.114	1.120	0.249	0.162	3.270
5	1.081	1.097	0.133	0.053	1.782	11	0.577	0.665	0.351	0.089	2.307
6	1.560	1.564	0.194	0.081	2.084	median r (g)					
7	1.086	1.104	0.139	0.064	1.768	1	1.002	1.010	0.095	0.005	1.336
8	1.249	1.261	0.181	0.079	1.819	2	0.999	1.000	0.095	0.009	1.327
9	0.287	0.303	0.203	-0.322	1.151	3	1.004	0.970	0.140	0.004	1.292
10	1.150	1.166	0.152	0.068	2.139	4	1.001	1.003	0.095	0.007	1.306
11	1.263	1.293	0.205	0.122	1.826	5	1.003	1.010	0.095	0.005	1.342
min z (g)						6	0.996	1.004	0.094	0.007	1.351
1	0.908	0.895	0.129	-0.488	1.141	7	1.004	1.010	0.095	0.005	1.345
2	0.612	0.581	0.169	-0.174	1.012	8	1.003	0.953	0.161	0.003	1.243
3	0.739	0.700	0.213	-0.156	1.018	9	1.006	0.912	0.223	0.004	1.444
4	0.707	0.677	0.163	-0.443	1.080	10	1.004	0.992	0.106	0.004	1.143
5	0.864	0.835	0.154	-0.140	1.197	11	1.003	1.010	0.095	0.004	1.360
6	0.575	0.522	0.750	-14.380	1.946	mean r (g)					
7	0.865	0.842	0.138	-0.177	1.026	1	1.002	1.010	0.095	0.005	1.338
8	-0.202	-0.200	0.209	-0.887	0.483	2	1.005	1.006	0.095	0.006	1.331
9	0.001	-0.001	0.215	-1.020	0.870	3	1.004	0.972	0.135	0.004	1.294
10	0.046	0.047	0.198	-1.313	0.646	4	1.005	1.004	0.097	0.006	1.320
11	0.714	0.628	0.282	-0.628	1.101	5	1.003	1.011	0.095	0.005	1.343
range z (g)						6	1.008	1.018	0.095	0.006	1.360
1	0.119	0.146	0.124	0.025	1.236	7	1.003	1.011	0.095	0.005	1.348
2	0.778	0.824	0.269	0.159	2.033	8	1.007	0.958	0.147	0.003	1.232
3	0.238	0.284	0.165	0.074	1.220	9	1.006	0.913	0.222	0.004	1.442
4	0.502	0.535	0.204	0.089	2.227	10	1.005	0.978	0.121	0.003	1.216
5	0.214	0.262	0.187	0.065	1.566	11	1.003	1.011	0.095	0.005	1.362
6	0.992	1.041	0.765	0.118	15.798						

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 4D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 5 of 6.

mvt	median	mean	s.d.	min	max
standard deviation r (g)					
1	0.008	0.010	0.007	0.002	0.087
2	0.110	0.119	0.041	0.015	0.314
3	0.018	0.023	0.018	0.006	0.232
4	0.082	0.087	0.030	0.016	0.204
5	0.017	0.021	0.023	0.005	0.324
6	0.154	0.154	0.037	0.015	0.571
7	0.019	0.022	0.013	0.005	0.134
8	0.103	0.131	0.072	0.014	0.390
9	0.016	0.021	0.016	0.005	0.180
10	0.067	0.097	0.069	0.008	0.361
11	0.044	0.052	0.042	0.007	0.683
max r (g)					
1	1.072	1.084	0.121	0.034	1.714
2	1.478	1.513	0.238	0.126	2.594
3	1.114	1.106	0.148	0.058	1.600
4	1.269	1.286	0.158	0.060	2.332
5	1.118	1.144	0.145	0.055	1.924
6	1.638	1.693	0.847	0.091	14.384
7	1.121	1.149	0.144	0.046	1.882
8	1.404	1.418	0.201	0.083	2.077
9	1.088	1.022	0.213	0.053	1.646
10	1.236	1.260	0.161	0.055	2.198
11	1.345	1.415	0.911	0.120	19.007
min r (g)					
1	0.954	0.946	0.103	0.031	1.217
2	0.741	0.718	0.150	0.071	1.163
3	0.901	0.852	0.152	0.068	1.156
4	0.826	0.805	0.118	0.042	1.149
5	0.904	0.888	0.126	0.047	1.254
6	0.610	0.603	0.096	0.055	0.963

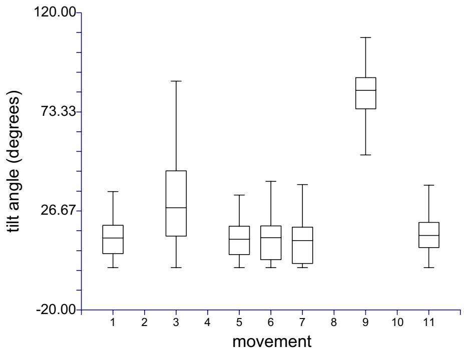
mvt	median	mean	s.d.	min	max
min r (g)					
7	0.900	0.890	0.118	0.047	1.051
8	0.718	0.635	0.217	0.056	0.954
9	0.916	0.815	0.242	0.044	1.309
10	0.802	0.714	0.208	0.041	0.940
11	0.782	0.759	0.144	0.065	1.175
range r (g)					
1	0.109	0.139	0.119	0.026	1.219
2	0.738	0.795	0.280	0.169	2.016
3	0.207	0.253	0.164	0.052	1.506
4	0.463	0.482	0.170	0.087	1.882
5	0.202	0.257	0.187	0.073	1.546
6	1.039	1.090	0.846	0.117	13.681
7	0.215	0.259	0.174	0.030	1.557
8	0.736	0.783	0.300	0.121	1.614
9	0.185	0.206	0.122	0.026	1.006
10	0.473	0.546	0.251	0.078	1.869
11	0.560	0.656	0.936	0.090	18.356
step rate (samples)					
med (2)	45.00	45.60	22.36	9.03	348.00
med (3)	26.00	32.15	28.81	1.16	360.00
mn(1)	1.75	2.77	18.94	0.06	356.00
mn (2)	48.15	53.11	25.98	6.69	348.00
mn (3)	34.94	40.37	28.35	3.69	360.00
sd (2)	25.09	30.85	28.53	5.79	348.00
sd (3)	21.84	26.14	31.42	4.24	439.82

Median, mean, standard deviation, min and max for parameters across all repetitions for all subjects by movement in study 4D. Movements are: 1. stand; 2. stand-to-sit; 3. sit; 4. sit-to-stand; 5. stand; 6. walk; 7. stand; 8. stand-to-lie; 9. lie; 10. lie-to-stand; 11. stand. Page 6 of 6.

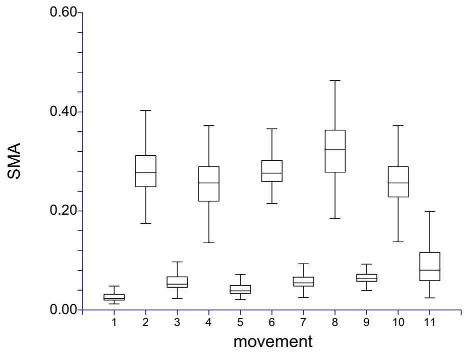
	median	mean	s.d.	min	max
frequency (Hz)					
x-axis	0.24	0.27	0.11	0.00	1.41
y-axis	0.24	0.29	0.13	0.00	1.38
z-axis	0.23	0.28	0.22	0.00	1.43
signal-to-noise ratio					
x-axis	48	57	35	0	248
y-axis	44	47	22	0	215
z-axis	18	20	15	0	130
interquartile range					
x-axis	0.017	0.027	0.046	0.006	0.824
y-axis	0.016	0.021	0.028	0.005	0.433
z-axis	0.010	0.012	0.009	0.005	0.109
magnitude	0.008	0.010	0.004	0.005	0.053

Parameters of postural sway measured during 30 s of quiet standing: sway frequency, magnitude of frequency peak and interquartile range

of sway acceleration. Overall median, mean, standard deviation, min and max are given across all repetitions of the routine by all subjects in study 4D.



(a)



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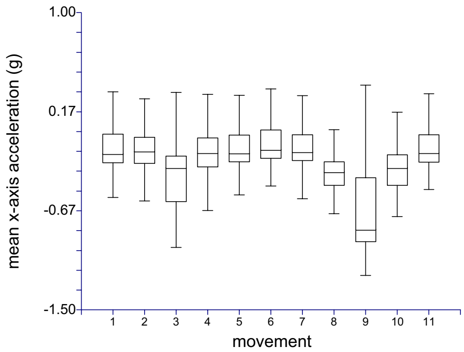

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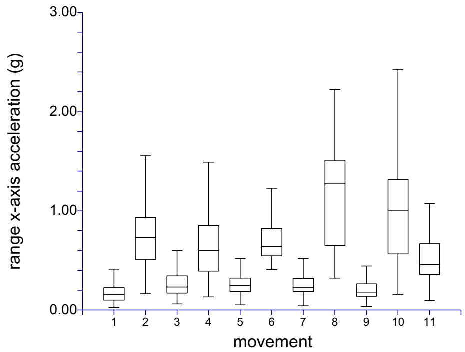

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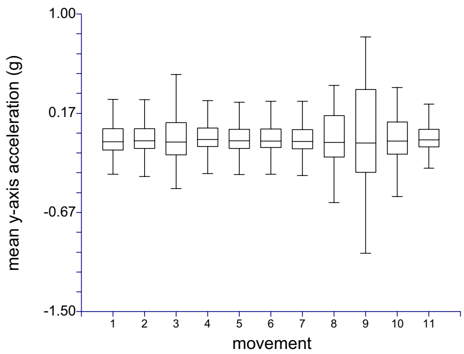

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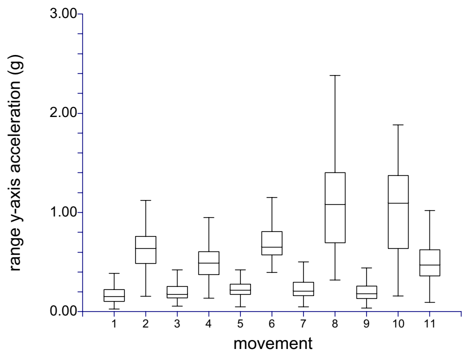
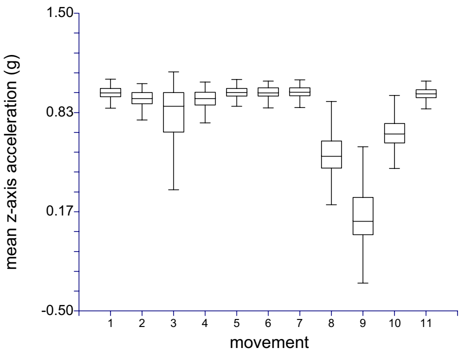
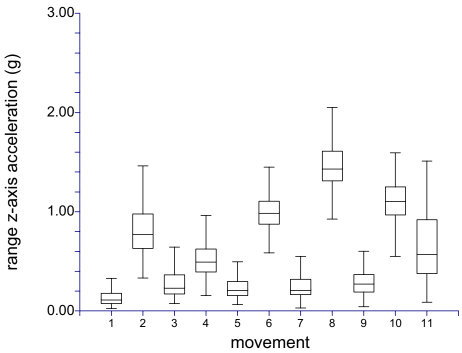


(f)

Boxplots comparing mean values for each activity across all repetitions for all subjects ($N = 6$) by movement in study 4D: (a) tilt angle; (b) SMA; (c) mean x-axis acceleration; (d) x-axis range; (e) mean y-axis acceleration; (f) y-axis range. Movements are 1: stand, 2: stand-to-sit, 3: sit, 4: sit-to-stand, 5: stand, 6: walk, 7: stand, 8: stand-to-lie, 9: lie, 10: lie-to-stand, 11: stand. Page 1 of 2.



(g)



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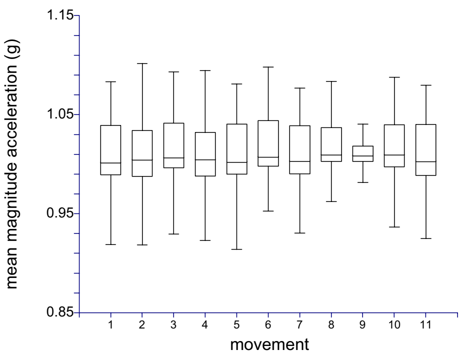
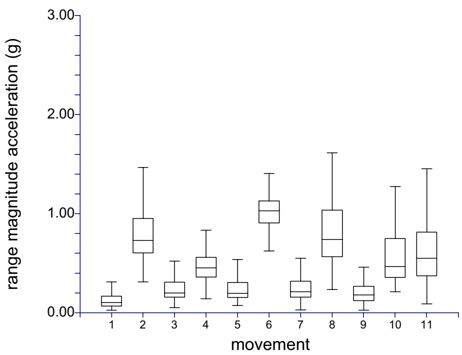
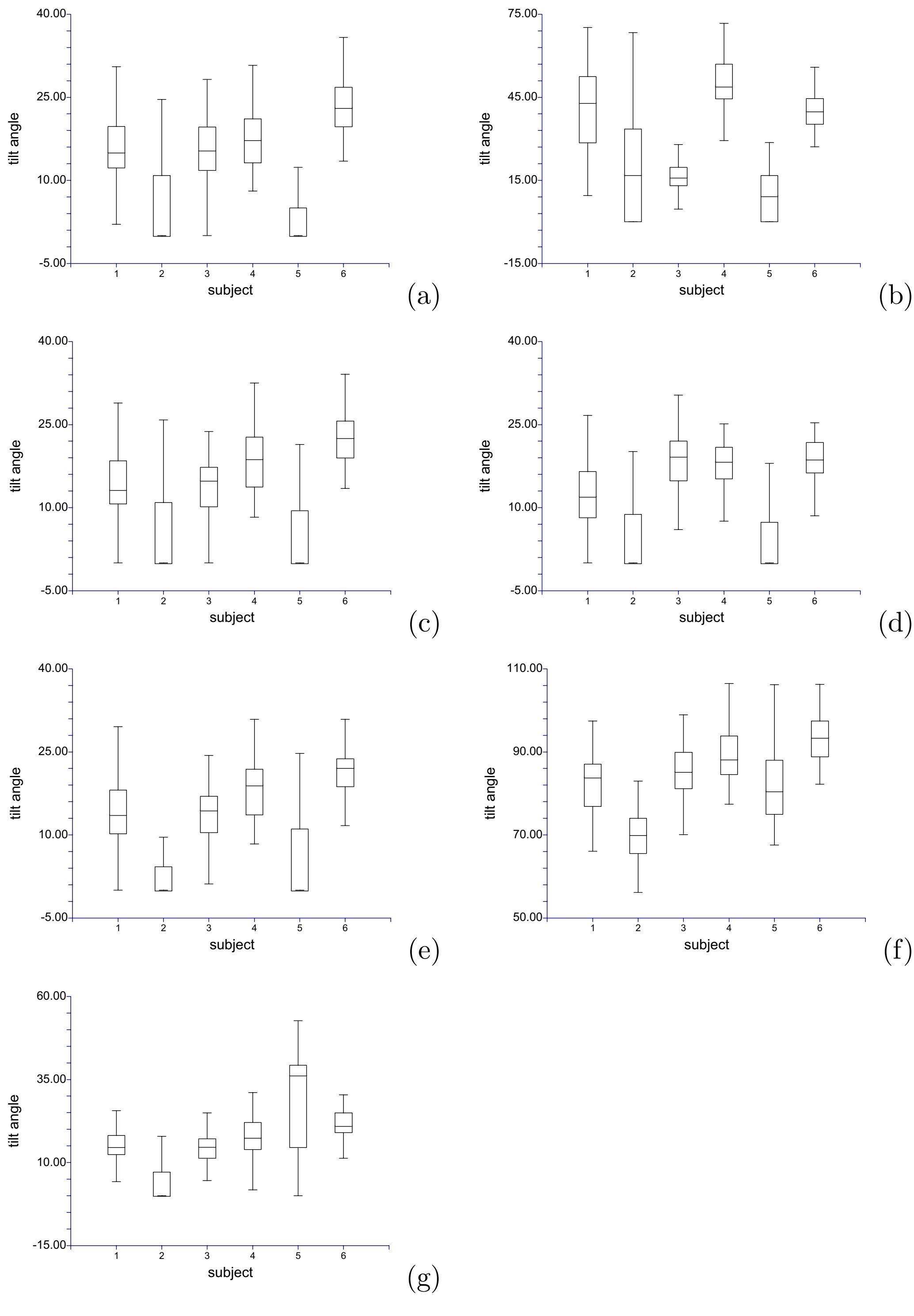


(i)

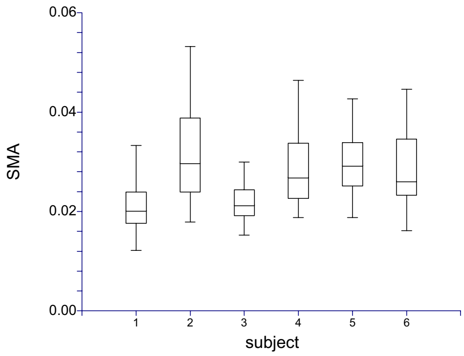


(j)

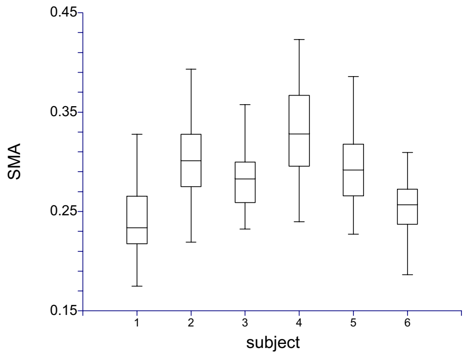
Boxplots comparing mean values for each activity across all repetitions for all subjects ($N = 6$) by movement in study 4D: (g) mean z-axis acceleration; (h) z-axis range; (i) mean magnitude acceleration, ρ; (j) magnitude acceleration, ρ, range. Movements are 1: stand, 2: stand-to-sit, 3: sit, 4: sit-to-stand, 5: stand, 6: walk, 7: stand, 8: stand-to-lie, 9: lie, 10: lie-to-stand, 11: stand. Page 2 of 2.



Boxplots of mean tilt angle for each subject ($N = 6$) in study 4D for each of the movements in the daily routine. Movements are (a) stand; (b) stand-to-sit; (c) sit; (d)sit-to-stand; (e) stand; (f) walk; (g) stand; (h) stand-to-lie; (i) lie; (j) lie-to-stand; and (k) stand. Note the different vertical axis scales between the graphs.



(a)



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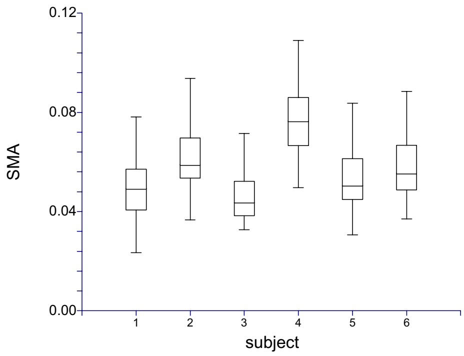

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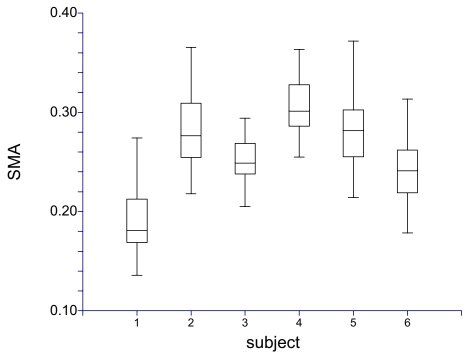

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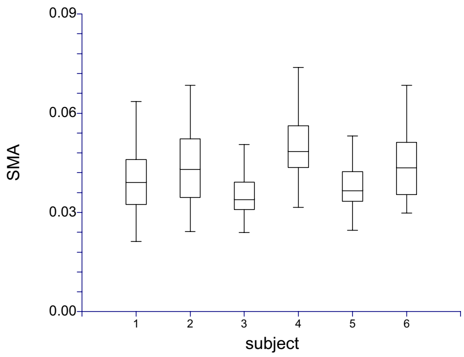
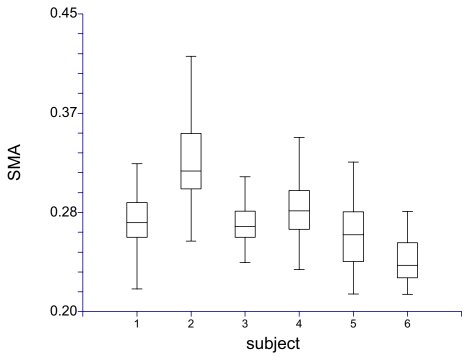
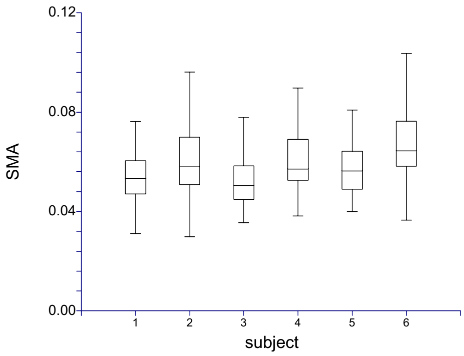


(e)

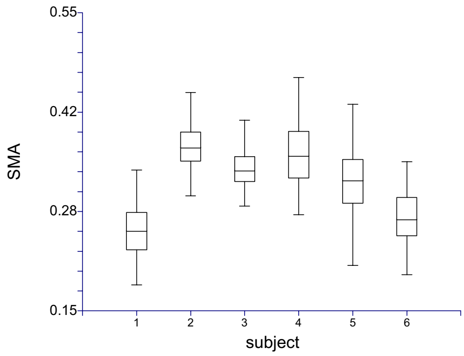


(f)

Boxplots of mean SMA for each subject ($N = 6$) in study 4D for each of the movements in the daily routine. Movements are: (a) stand; (b) stand-to-sit; (c) sit; (d) sit-to-stand; (e) stand; (f) walk. Note the different vertical axis scales between the graphs. Page 1 of 2.



(g)



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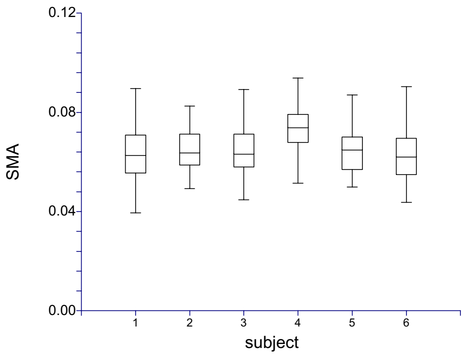
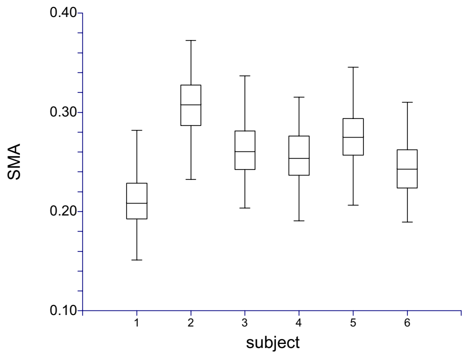
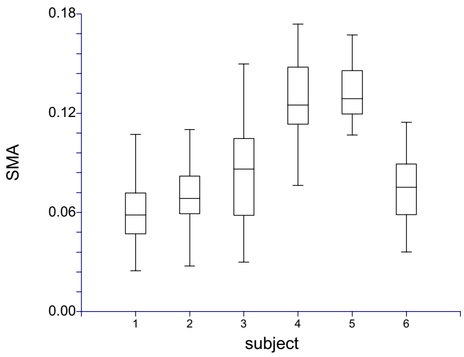


(i)



(j)



(k)

Boxplots of mean SMA for each subject ($N = 6$) in study 4D for each of the movements in the daily routine. Movements are: (g) stand; (h) stand-to-lie; (i) lie; (j) lie-to-stand; and (k) stand. Note the different vertical axis scales between the graphs. Page 2 of 2.

Appendix G

List of Publications

JOURNAL

- Mathie, M.J.; Coster, A.C.F.; Lovell, N.H.; Celler, B.G. Classification of basic daily movements using a triaxial accelerometer, *Medical and Biological Engineering and Computing*, Accepted for publication in 2004.

- Mathie, M.J; Coster, A.C.F.; Lovell, N.H.; Celler, B.G. Accelerometry: Providing an integrated, practical method for long-term, ambulatory monitoring of human movement, *Physiological Measurement*, 25:R1-R20, 2004.

- Mathie, M.J.; Coster, A.C.F.; Lovell, N.H.; Celler, B.G. A pilot study of long-term monitoring of human movements in the home using accelerometry, *Journal of Telemedicine and Telecare*, 10(3):144-151, 2004.

- Mathie, M.J; Coster, A.C.F.; Lovell, N.H.; Celler, B.G. Detection of daily physical activities using a triaxial accelerometer. *Medical & Biological Engineering & Computing*, 41(3):296-301, 2003.

CONFERENCE

- M.J. Mathie, A.C.F. Coster, N.H. Lovell and B.G. Celler. Design of a study for unsupervised monitoring using a triaxial accelerometer. *World Congress on Medical Physics and Biomedical Engineering*, Sydney, Australia, August 2003.

- M.J. Mathie, A.C.F. Coster, N.H. Lovell and B.G. Celler. Use of a triaxial accelerometer in unsupervised monitoring of human movement. *World Congress on Medical Physics and Biomedical Engineering*, Sydney, Australia, August 2003.

- M.J. Mathie, A.C.F. Coster and B.G. Celler. Determining walking activity using a triaxial accelerometer. *2nd European Medical & Biological Engineering Conference EMBEC'02*, Vienna, Austria, December 2002.

- M.J. Mathie, N.H. Lovell, A.C.F. Coster and B.G. Celler. Determining Activity Using a Triaxial Accelerometer. *2nd Joint EMBS-BMES Conference*, Houston, USA, October 2002.

- M.J. Mathie, J. Basilakis and B.G. Celler. A system for monitoring posture and physical activity using accelerometers. *23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society,* Istanbul, Turkey, October 2001.

- M.J. Mathie, B.G. Celler, J. Basilakis, N.H. Lovell, F. Magrabi and K. Huynh. A specification for a home telecare system for patients with congestive heart failure. *Proceedings of the 10th International Conference on Biomedical Engineering*, Singapore, December 2000.

- B.G. Celler, N.H. Lovell, M.J. Mathie, J. Basilakis, R. Salleh, F. Magrabi, Ambulatory monitoring and real time diagnosis of clinical data. *HIC 2000: Integrating Information for Health Care*, Adelaide, Australia, September 2000.