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Publication Date:
2011

DOI:
https://doi.org/10.26190/unsworks/23814

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THE UNIVERSITY OF NEW SOUTH WALES

Evaluation of falls risk using a single, waist-mounted tri-axial accelerometer

A dissertation submitted for the degree of doctor of philosophy

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2011

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Acknowledgements

To my supervisors, Prof Nigel Lovell and Prof Branko Celler, thank you both for your untiring guidance and encouragement as well as imparting a sense of scientific rigor to my work. Thank you for providing me with the freedom to explore and an opportunity to work alongside you.

My gratitude extends to Dr Stephen Redmond for proofreading this thesis and reviewing my work and help in analysing the clinical trial data. I would also like to give special thanks to Maria Elena Scalzi for assisting in the clinical trial and analysis of the clinical trial data. This work would have never been finished if it was not for the help from you both.

I would like to thank Prof Stephen Lord, Dr Kim Delbaere and the staff at the Prince of Wales Medical Research Institute for allowing me to conduct a clinical trial at the falls clinic and providing constant support and guidance.

I would like to thank my colleagues at the Biomedical Systems Laboratory, in particular Dean Karantonis, Louis Jung, David Chang, Ning Wang, Arridh Shashank, Arjuna Vijayanayagam, James Zhang, Rudi Voon, Daoming Zhang and Stephen Ong, for all the cups of coffee, conversations, wonderful memories and creating an excellent environment in which to work.

Finally, I would like to thank my wife and parents for their endless support and encouragement and having to listen to me talk about my research nonstop for the duration of my candidature.

Abstract

Falls among the elderly population are a major cause of morbidity and mortality. Approximately one in three people, over the age of 65, fall each year. Falls result in a reduction in one's overall quality of life, not only as a result of injuries, but from a restriction in activity due to a fear of falling and loss of independence. Falls are a leading cause of hospitalisation among the elderly and place a significant burden on healthcare systems. Validated clinical tests and associated models, built upon assessment of functional ability, have been devised to estimate an individual's risk of falling in the near future. Those identified as at-risk of falling may be targeted for interventative treatment. The migration of these clinical models estimating falls risk to a surrogate technique, for use in the unsupervised environment, might broaden the reach of falls risk screening beyond the clinical arena. This study details an approach which characterises the movements of 68 elderly subjects performing a directed routine of unsupervised physical tasks. The movement characterisation is achieved through the use of a single tri-axial accelerometer-based ambulatory monitor attached to the waist. A number of falls related features, extracted from the accelerometry signals, combined with a linear least squares model, maps to a clinically validated measure of falls risk with a correlation of $\rho = 0.80$ ($p < 0.001$). The extracted features were also mapped to the scores obtained from assessment of knee-extension strength, body sway, edge contrast sensitivity and proprioception, with correlations of $\rho = 0.65$ ($p < 0.001$), $\rho = 0.58$ ($p < 0.001$), $\rho = 0.46$ ($p < 0.001$) and $\rho = 0.30$ ($p < 0.05$), respectively. The results show the potential of body-worn sensors to evaluate falls risk and falls risk factors in an objective and deterministic

manner. The unsupervised assessment enables falls risk to be tracked longitudinally, opening up opportunities for the improvement management of falls in the elderly.

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1 Introduction

Falls in the elderly are major public health challenge facing numerous countries and exacerbated by a rapidly ageing global population. One in three, community-dwelling elderly, over the age of 65 fall each year with the likelihood of falling increasing with age. The consequences of falls can be quite severe. Falls are a leading cause of injury based hospitalisations in the elderly often resulting in cuts, abrasions and fractures and can lead to premature institutionalisation. Aside from the physical, falls can have severe psychological effects. The fear of falling alone can cause a restriction of activity in the elderly. Falls result in a reduced quality of life in the elderly. Apart from the affect on the individual, falls come at a tremendous cost to the healthcare system, utilising a variety of healthcare resources in the treatment of the effects of falls and the ongoing costs of rehabilitation and aged care. Considerable effort has been made to develop means to reduce the risk, rate and severity of falls in the elderly.

Falls in the elderly has been a heavily researched area over recent decades, with an immense body of knowledge developed. The overall aim of the research is quite clear, to implement preventative strategies that will reduce ones risk of falling, reduce the rate of falling and prevent severe falls that have the most impact on the mortality and morbidity of the elderly community. To achieve this, research has elucidated the risk factors that predispose falls in the elderly, developed risk assessments to quantify ones risk of falling and thus identify those at risk. Intervention strategies targeted at the 'at risk' elderly have

been developed with the aim of reducing ones risk, rate and severity of falls. Coupling the knowledge of falls risk factors, falls risk assessment and intervention are the strategies for prevention that look to target the elderly at risk of falls and apply appropriate interventions.

In tandem with the progression of falls research, advances in sensor technology and embedded systems have enabled sophisticated, highly portable, body-worn ambulatory monitoring systems to be developed that evaluate and characterise movement of the human body. Numerous systems, targeted toward the elderly have been developed, including systems to monitor activity levels, classify motion, evaluate balance, evaluate gait function and detect falls.

A guideline for the prevention of falls in the elderly developed by the American and British geriatric societies and the American Academy of Orthopedic Surgeons, described an algorithm for the assessment and management of falls [1]. The algorithm, shown Figure 1.1, depicts the management of falls in which elderly are identified as needing falls risk evaluation based on falls history and a simple assessment of balance and gait. The falls risk evaluation identifies risk factors for falls that can be used to develop multifactorial interventions. This algorithm highlights the potential utility of ambulatory monitors in the management of falls in the elderly. An ambulatory monitor capable of identifying elderly at risk of falls and identifying clinically relevant falls risk factors would be immensely useful in the management of falls and is shown in Figure 1.2.

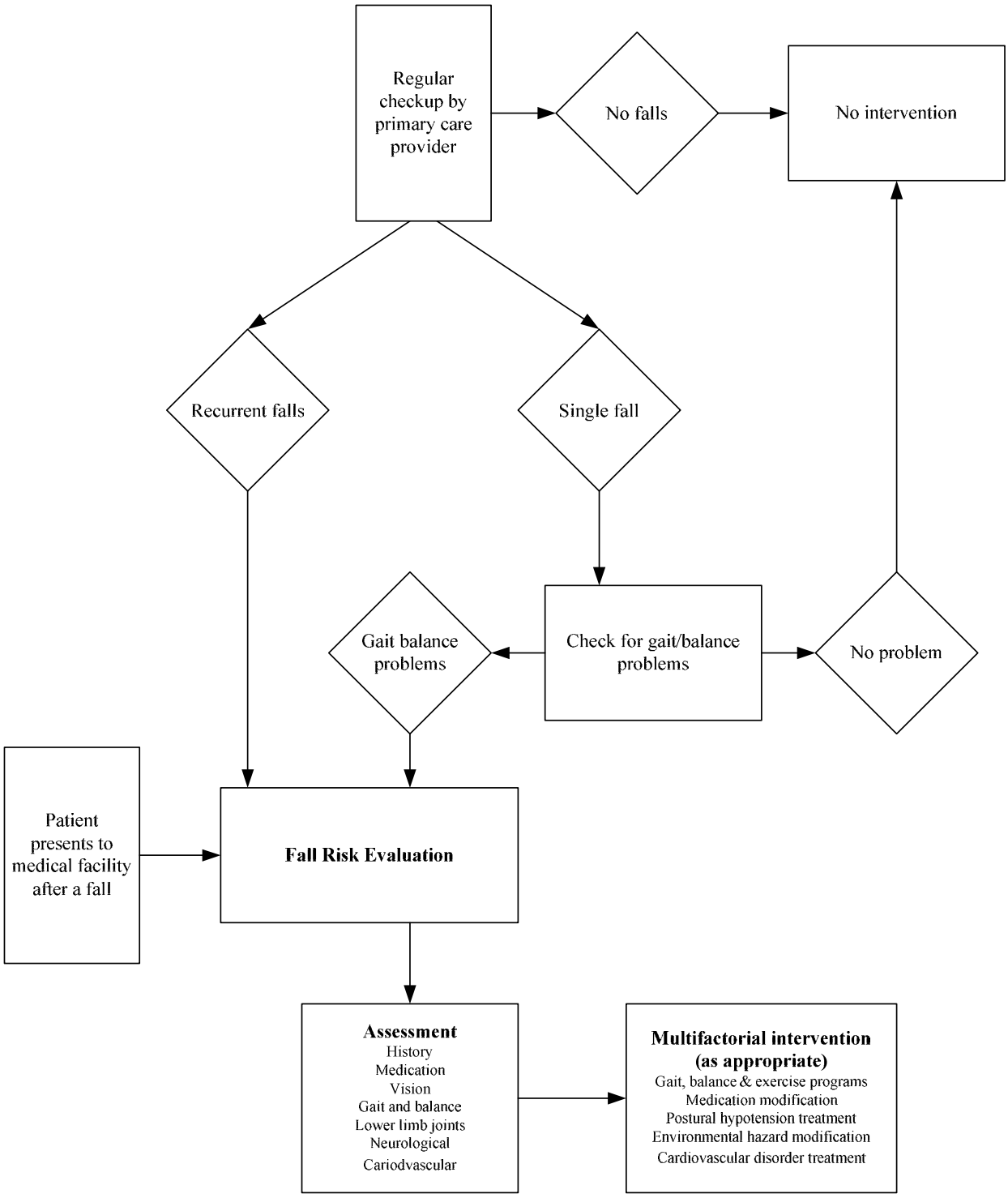


Figure 1.1 - Algorithm for the management of falls in the elderly, based on identifying at risk elderly, falls risk factor evaluation and intervention. Adapted from [1].

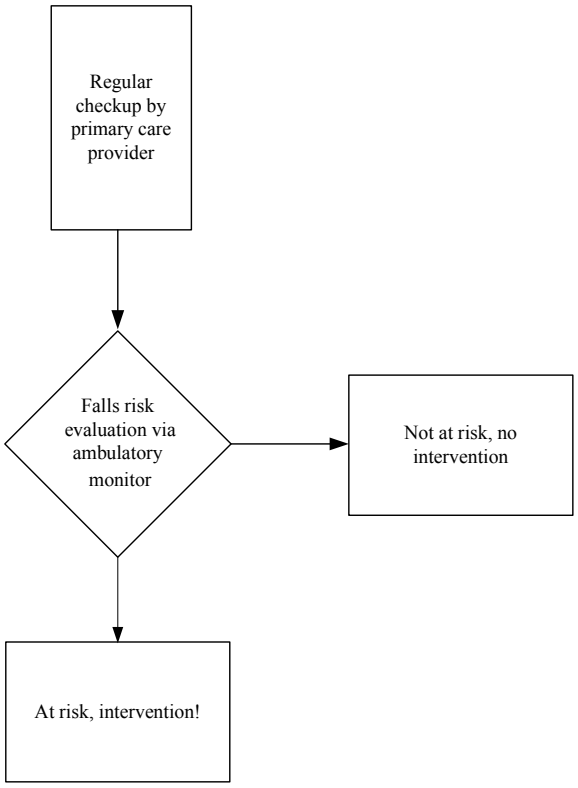


Figure 1.2 - Alternate algorithm for the management of falls using an ambulatory monitor to identify elderly at risk and evaluate falls risk factors.

Elderly are assessed for falls risk and risk factors using the ambulatory monitor, with interventions formed on the basis of the assessment.

This notion of falls risk assessment and risk factor assessment, forms the basis for the hypothesis of this thesis, that a single waist-mounted tri-axial accelerometer-based ambulatory monitor can be used for the unsupervised assessment of falls risk in the elderly and for falls risk factor assessment in the elderly. A system designed to be used unsupervised by the elderly, has more restrictions than a system designed to be administered by trained personal but has the potential to provide long-term falls

management for the elderly. In addition a system that can be used unsupervised can be used supervised. The opposite, is definitely not true.

Chapter two provides background on falls in the elderly in terms of clinical research and application of wearable monitors. The ramifications of falls, falls risk factors, assessment of falls risk and interventions to reduce falls risk are described. The application of wearable devices to detect falls, evaluate mobility in the elderly and evaluate falls risk is presented.

Chapter three describes the tri-axial accelerometer-based ambulatory monitor developed for this study. The requirements and design of the ambulatory monitor, as well as, the requirements and design of a clinical monitoring system and home monitoring system that incorporates the ambulatory monitor are presented. Additionally, an understanding of the acceleration signal, provided by the ambulatory monitor, is provided.

Chapter four provides the rationale for the assessment of falls risk in the elderly and evaluates the types of movement data that can be captured in a free-living, unsupervised environment. The movements selected for evaluation are described. The chapter concludes with the design of the clinical study, involving a cohort of community-dwelling elderly, used to develop a falls risk assessment tool using a single waist-mounted ambulatory monitor.

Chapters five provides the analysis of the clinical study data and describes the parameters extracted from the acceleration data that are used to model falls risk and functional ability in the elderly. Chapters six and seven present the results, discussion and conclusions of the work, respectively.

2 Falls in the elderly

2.1 The problem

Falls in the elderly are a major public health challenge. The implications and consequences of falls are severe. Falls can greatly affect the quality of life for the elderly with the implications for individuals including injury, psychological damage, hospitalisation and even institutionalisation. The implications for society include the cost to the health care system, in terms of treatment, prevention and ongoing costs of care.

The incidence of falls has been studied extensively in the elderly population [2-6]. Studies have evaluated the incidence of falls in a number of target populations, including the community-dwelling elderly, hospitalised and institutionalised elderly and in those with particular pathologies such as stroke or Parkinson's disease [3]. The incidence for falls in the elderly population is high and varies with living status and morbidity and increases significantly with age [3]. It is generally accepted that one in three community-dwelling elderly over the age of 65 fall at least once each year [3]. Schummway-Cook *et al.* [5], in a survey of 12669 community-dwelling elderly over the age of 65, found that 22.1% of the population fell at least once each year, with 10% suffering multiple falls. Rubenstein [4] on the other hand, reported 40% of community-dwelling elderly over the age of 65 fall each year with a mean rate of falls of 0.65 for community-dwelling elderly compared with a mean rate of 1.7 falls in the institutionalised. Lord *et al.* [3], reported a

rate of falls of elderly people in residential care as much as three times higher than community-dwelling elderly.

In terms of hospitalization, it has been reported that as much as 5% of falls in community-dwelling elderly result in hospitalisation with the figure rising to 10-25% in the institutionalised elderly [4]. Laird *et al.* [7] found that the frequency of falls was an independent predictor of hospitalisation in the elderly. In a report on hospitalisations due to falls in 2005-06 [2], produced by the Australian Institute of Health and Welfare (AIHW) on behalf of the Australian Government, it was estimated that 2415 per 100000 elderly over the age of 65 were hospitalised as a result of falls each year. Significantly higher than the rate (1688/100000) seen in the United Kingdom [8]. The report found that elderly in residential care had five times the rate of hospitalisation (7235.5/100000). This represented 2.6% of all hospitalisations in those over the age of 65, with approximately half the falls occurring at home and most commonly due to slips, trips and stumbles. More worryingly though, is that they found the age-standardised rate of falls increased in the 2005-06 period (2415/100000) from 2295/100000 in 2003-04 and that the estimated total length of stay per fall also increased. That is, the elderly are being hospitalised more frequently and staying longer in hospital as a result of falls.

Falls are the cause of a variety of injuries, of varying severity in the elderly. The most commonly self-reported injuries include cuts, abrasions, bruises and sprains [3]. The more serious injuries resulting from falls, include fractures of the hip, pelvis, legs, arms, hands, ribs and vertebrae, as well as, joint injuries and intracranial injuries [3, 6]. Injuries from falls often result in a restriction of activity and hospitalization [6]. Perhaps the most

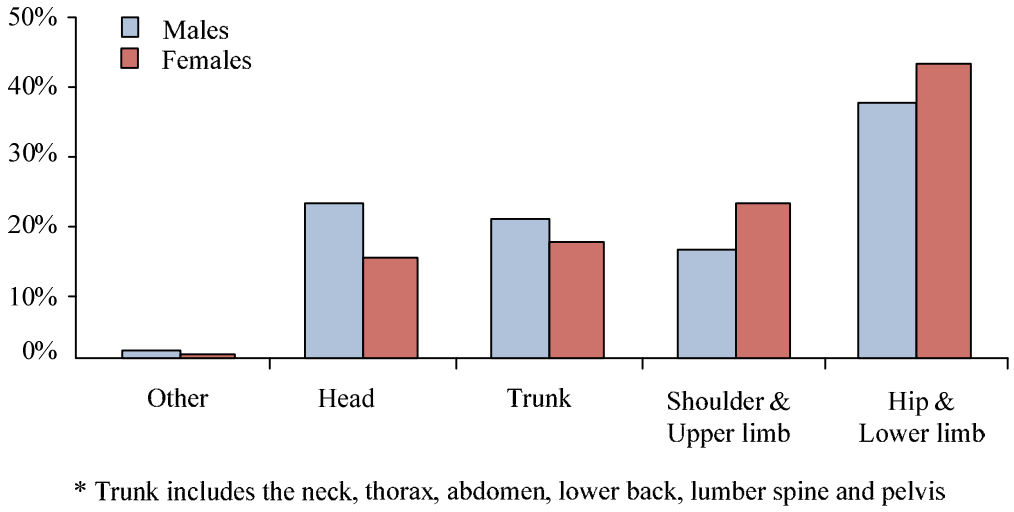


Figure 2.1 - Distribution of injury types in an estimated 66800 hospitalised elderly over the age of 65. Adapted from [2].

serious of injuries associated with falls are hip fractures. Such fractures are a significant cause of mortality in the elderly [9-11]. In a AIHW report on hospitalisations due to falls in Australia in 2005-06 [2], it was found that the most common injury types, in an estimated 66800 cases of hospitalization due to falls, were injuries to hip and thigh (31%), injuries to the head (17%), injuries to the abdomen, lower back, lumbar spine and pelvis (11%), injuries to the elbow and forearm (10%), injuries to the shoulder and upper arm (10%) and injuries to the knee and ankle (10%). This represents 89% of all cases and is illustrated in Figure 2.1.

Injuries are not just physical, with a number of psychological affects attributed to falls. Tinetti *et al.* [12] showed falls lead to a decline in function, not only as a result of physical injury, but in part as a result of a loss of confidence to perform functional tasks. Delbaere *et al.* [13], found that catastrophic thoughts about falls was a predictor for

concerns for falls, which, in turn was associated with mobility restriction in the elderly. Delbaere *et al.* [14], also reported that fear-related avoidance of activity is associated with physical performance in the elderly, and that fear of falling and the restriction of activity were predictive of falls in a 1-year prospective study of 225 community-dwelling elderly. What was also interesting about the study was that the fear of falling existed in those who had never experienced a fall.

The health care costs of falls in the elderly have been evaluated in a number of studies [2, 5, 8, 15-16]. The significant cost associated with falls is obvious when considering the array of injuries associated with falling [2-3, 6]. Rizzo *et al.* [15], showed that the costs of falls increase with the frequency and severity of falls. Apart from the costs associated with the treatment of falls, there are the ongoing costs associated with rehabilitation and the costs associated with those placed into residential care facilities, nursing homes and other institutions. It has been shown that falls are an independent risk factor for nursing home admission and institutionalisation in the elderly [6-7]. In Australia alone, the direct costs attributed to treatment of falls in those hospitalised was found to be $566 million, with the total costs expected to exceed $1 billion when factoring the associated indirect costs [2]. Stevens *et al.* [16], reported the direct medical costs for 2.6 million medically treated non-fatal injurious falls in the year 2000 was $19 billion. Interestingly, they found that 35% of the injuries treated were fractures and that the treatment of fractures accounted for 61% of the total direct costs. It is not surprising that a concerted effort is made to reduce the rate and severity of falls in the elderly to help curb the rising costs of falls.

2.2 Risk factors for falls

Numerous risk factors for falls have been identified through retrospective and prospective epidemiological studies. Risk factors are classified as either:

- intrinsic, such as muscle strength, vision and peripheral sensation or,
- extrinsic, such as use of an assistive device, medications and environmental factors such as uneven surfaces and poor lighting.

One's overall risk relates to the combination of intrinsic and extrinsic risk factors to which they are exposed to.

The ability to coordinate muscle activity in order to maintain static and dynamic balance is fundamental to the avoidance of falls. To achieve this, sensory information is integrated and processed in the brain, to determine and deliver the appropriate stimuli to the musculoskeletal system to coordinate muscle activity and generate the necessary movements to maintain balance. Figure 2.2 shows the primary, physiological factors, contributing to the maintenance of balance. Somatosensations providing information on tactile sensation such as touch, pressure and vibration sense as well as proprioception providing information about how much muscles are contracted, the amount of tension in tendon organs, position of joints and orientation of the head coupled with vestibular sense, providing of static and dynamic position relative to gravity, and vision, are integrated in the brain to provide a sense of orientation and position in space that is used to coordinate muscle activity to ensure stability is maintained. Deficits in these functions have been shown to contribute to increased falls risk in the elderly.

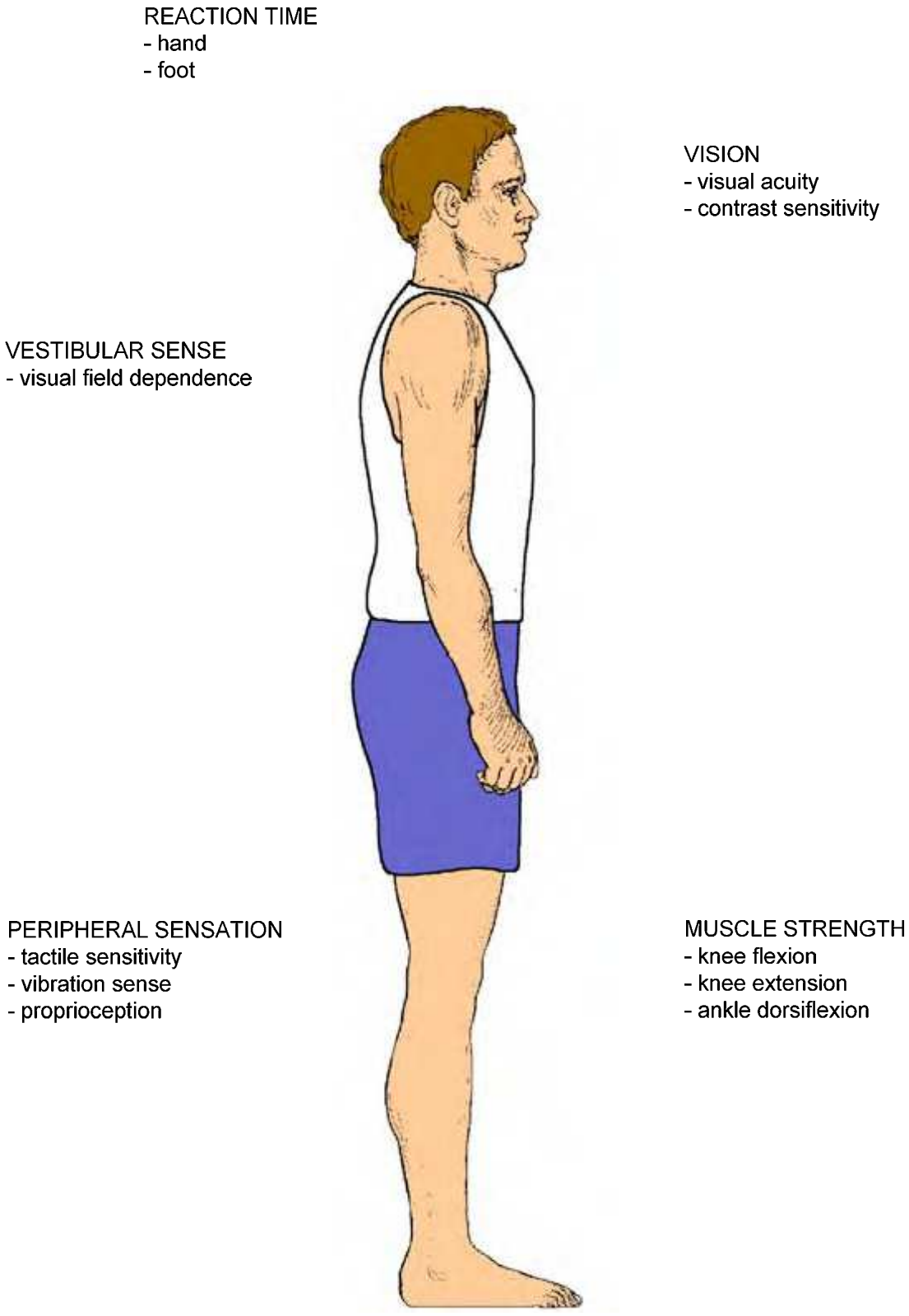


Figure 2.2 - Physiological system contributing to the maintenance of balance. Adapted from [17].

Vision impairment has been shown to be an independent and significant risk factor for falls in the elderly. Measures of low contrast sensitivity, low contrast visual acuity and depth perception are amongst the more strongly associated vision risk factors for falling and recurrent falling in the elderly [18-23]. Lord *et al.* [21], suggested that low contrast sensitivity, which is the ability to detect edges in low contrast conditions, may relate to one's ability to detect ground level hazards. Similarly, depth perception, which is the ability to perceive space in 3-dimensions, was found to be a strong risk factor for recurrent falls, with low rates occurring in those with relatively good vision in both eyes and the highest rates in those with poor vision in both eyes. It was suggested that depth perception was important for negotiating hazards in the environment [21].

Somatosensation provides important proprioceptive sensory information regarding the contraction of muscles, position of joints, tension in tendons and the orientation of the head as well as, information on tactile sensations of touch, pressure and vibration which enable us to perceive the nature of the environment. That is are we standing on a firm surface such as concrete or a more compliant surface such as sand? A number of studies have found deficits in somatosensation are associated with increased falls risk. In particular, reduced tactile sensitivity, poor vibration sense and poor proprioception were associated with fallers and multiple fallers in the elderly [20, 22, 24-25].

Vestibular function provides sensory information for the maintenance of static and dymamic equilibrium in order to maintain body position with respect to gravity, and in response to movement, respectively. Vestibular function has been investigated with

respect to falls in the elderly [24, 26]. Herdman *et al.* [26], found significantly increased incidence of falls in the elderly, aged between 65-75 years, with vestibular hypofunction when compared with healthy age-matched elderly.

Sensory inputs are translated, in the brain, into the movements required to maintain balance. The ability to generate sufficient muscle force is crucial to the maintenance of balance [27]. Muscle strength is an important risk factor for falls in the elderly and studies that have included strength testing have consistently found muscle weakness to be a significant risk factor for falls [28]. A number of studies have shown lower-limb strength, including quadriceps strength, ankle dorsiflexion strength, and knee-extension strength are associated with increased falls risk in the elderly [20, 22, 24, 27, 29].

In addition to vision, vestibular function, peripheral sensation and muscle strength, reaction time has been shown to be another basic physiological function associated with falling in the elderly. Poor reaction time may affect one's ability to react to visual stimuli or perturbation of balance, resulting in increased falls risk. Multiple fallers, in particular, have been shown to have significantly slowed reaction time when compared to single-fallers and non-fallers [20, 22].

Alongside the fundamental physiological risk factors for falls, a number of medical and medications-related falls risk factors have been identified. Particular morbidities have been shown to relate to increased falls risk in the elderly. In particular, neuromuscular disorders, urinary incontinence, arthritis, cognitive impairment, depression, stroke and

Parkinson's disease have all been shown to be associated with increased falls risk [1, 3, 30-31].

Medications use has been linked to increased falls risk in many studies. Postural ability, for example, has been shown to be affected by taking psychoactive and/or antihypertensive medications [24]. Benzodiazepines, antidepressants, antipsychotics, antiepileptics and central nervous system medications have been associated with an increased risk of falling [32-33]. Polypharmacy, which is the use of multiple medications, has also been shown to be a risk factor for falls in the elderly [32].

Impaired postural stability and balance has been studied extensively in the elderly and associated with falls risk. As shown, postural stability and balance may be affected for a variety of physiological, medical and medications related reasons. However, the presence of impaired balance has been shown to relate to increased falls risk in the elderly and has also been shown to be one of the more significant risk factors for falls [1]. Fallers and in particular recurrent fallers, have been shown to have increased body sway on firm and compliant surfaces, with eyes open and closed [20, 24].

Other risk factors for falls include environmental risk factors, such as absence of hand rails in the home, unsafe steps, uneven flooring and unsafe chairs [34], as well as demographic factors such as age, sex and living status [1, 3].

Identification of risk factors for falls is the precursor to falls risk screens and assessments as well as interventions targeting risk factors that are amenable. The following section evaluates falls risk screening and assessment tools described in the literature.

2.3 The assessment of falls risk

As described in the introduction, the American and British geriatric societies and the American Academy of Orthopedic Surgeons, described an algorithm, in a guideline for the prevention of falls in the elderly, for the assessment and management of falls [1]. The algorithm, which is shown in Figure 1.1, was derived from evidence showing association between risk factors for falls and from the positive outcomes of intervention studies, and presents the management of falls in terms of identifying those at risk, evaluating individual risk factors and applying appropriate intervention.

The algorithm suggests a simple mobility task, supplemented with falls history, be used to identify those at risk of falling. Those, at increased risk, are evaluated using a more comprehensive assessment of falls risk, evaluating factors such as medications, visual impairment, gait and balance. In this algorithm, history of falls and the mobility assessment are used as a falls screen, to identify those at risk of falling and the comprehensive evaluation as falls risk assessment to identify a variety of risk factors contributing to one’s overall risk.

The literature describes a number of tools used as falls risk screens and falls risk assessments. A variety of approaches have been taken, from simple questionnaires to functional mobility assessments of balance, coordination and strength, to multifactorial assessments incorporating assessments of vision, balance, strength, somatosensation and reaction time, for example. Tools vary in use, from those used to assess community-dwelling elderly to those designed to assess elderly in residential care or those in hospital settings. Some tools aim to stratify fallers from non-fallers while others look to identify recurrent fallers or those at risk of injurious falls. The described tools vary in the number of items assessed, from single item assessments to multiple item assessments. The time taken to complete the assessments ranges from a few minutes to well over an hour, with some assessments requiring no equipment, minimal equipment to a numerous pieces of equipment. Some equipment is quite simple to use, while others are quite sophisticated. Thus, some tools are better suited for use as quick screens than others.

This section describes a number of the falls risk screens and falls risk assessment described in the literature, with an emphasis on those used in the assessment of community-dwelling elderly.

2.3.1 Falls risk screening tools

The Timed Up-and-Go Test (TUGT) is a functional mobility assessment in which the subject under test stands from a seated position, walks three meters, turns around, walks back to the chair and sits down as quickly as possible [35]. The time taken to complete the TUGT is used as the performance score. The TUGT has been suggested as a quick assessment of functional ability to determine if further falls risk assessment is required. It has also been suggested as a quick screen for falls risk in the best practice guidelines for the prevention of falls and harm from falls in older people by the Australian Commission on Safety and Quality in Healthcare (ACSQHC) [36]. The test involves minimal equipment, only a chair, and is very quick to administer.

The TUGT has demonstrated reasonable accuracy in discriminating between fallers and non-fallers in a number of retrospective studies. Shumway-Cook *et al.* [37], in a study of 30 community-dwelling elderly, aged between 65-85 years, found that a score of greater than 13.5 seconds discriminated between multiple-fallers and non-fallers with a sensitivity of 80% and specificity of 100%. The authors concluded that the TUGT is a simple test sensitive and specific measure of the probability of falls that can be used to screen elderly for falls risk. Rose *et al.* [38], in a study of 134 community-dwelling elderly, aged between 60-90 years, found that the TUGT discriminated between fallers and non-fallers with a sensitivity of 86% and specificity of 71%. In a similar study conducted by Gunter *et al.* [39], involving 157 elderly subjects living independently in

the community, retirement villages or assisted living facilities found that TUGT scores correctly classified 71.2% of fallers in the study.

The Sit-To-Stand transfer with five repetitions (STS5) is a measure of lower limb strength, speed and coordination. The test is performed by completing five sit-to-stand transfers, with arms folded, as quickly as possible. The time taken to complete the task is used as the performance score [40]. Whitney *et al.* [41], found the STS5 to be a potentially useful clinical measure of balance disorder in the elderly, with the STS5 identifying 61% of those with balance dysfunction in a study of 174 elderly subjects between the ages of 61-90 years. A score of more than 12 seconds was found to be indicative of increased falls risk and was used to discriminate between multiple-fallers and non-multiple fallers in a prospective study of 362 community-dwelling elderly between the ages of 74-98 years [40]. The STS5 demonstrated a sensitivity of 66% and specificity of 55% in discriminating between the two faller groups. Like the AST, the STS5 only required a single piece of equipment and was demonstrated to be a feasible, reliable and valid initial screen for falls risk in the elderly. Tromp *et al.* [42], found the STS5 to be a predictor for elevated risk of falls in a prospective study of 1285 community-dwelling elderly.

The Alternate-Step Test (AST), a measure of lateral stability, involves placing the whole of each foot onto, and off of, a small platform 19 cm high and 40 cm wide as quickly as possible [40]. The time taken to complete the task is taken as the score. A score of more

than 10 seconds was used to discriminate between multiple-fallers and non-multiple fallers in a prospective study of 362 community-dwelling elderly between the ages of 74-98 years [40]. The AST demonstrated a sensitivity of 69% and specificity of 56%. The AST requires only a single, relatively simple, piece of specialised equipment, namely the stepping platform. The authors found the AST to be a reliable, valid and feasible tool for use an initial falls risk screen. The AST has been suggested as a quick falls risk screening tool in the ACSQHC guidelines for preventing falls [36].

Another stepping test is the Four Square Step Test (FSST) [43]. The test is an assessment of dynamic standing balance. The FSST, illustrated in Figure 2.3, involves stepping forwards, sideways and backwards in a grid defined by a pair of axes 90 cm long and 2.5 cm high. The test is performed with the subject starting in square 1 and facing square 2. The subject, steps forward into square 2, sideways into square 3, backwards into square 4, sideways into square 1, sideways into square 4, forwards into square 3, sideways into square 2 and backwards into square 1. The series of steps are performed with the subject facing forwards. The test is performed as quickly as possible, with the time taken to complete the FSST used as the performance metric.

The FSST was evaluated in a retrospective study involving 81 community-dwelling elderly subjects [43]. The FSST, demonstrated excellent reliability using interclass correlation coefficients (ICC), (n=30, ICC=0.99), and excellent test/retest reliability,

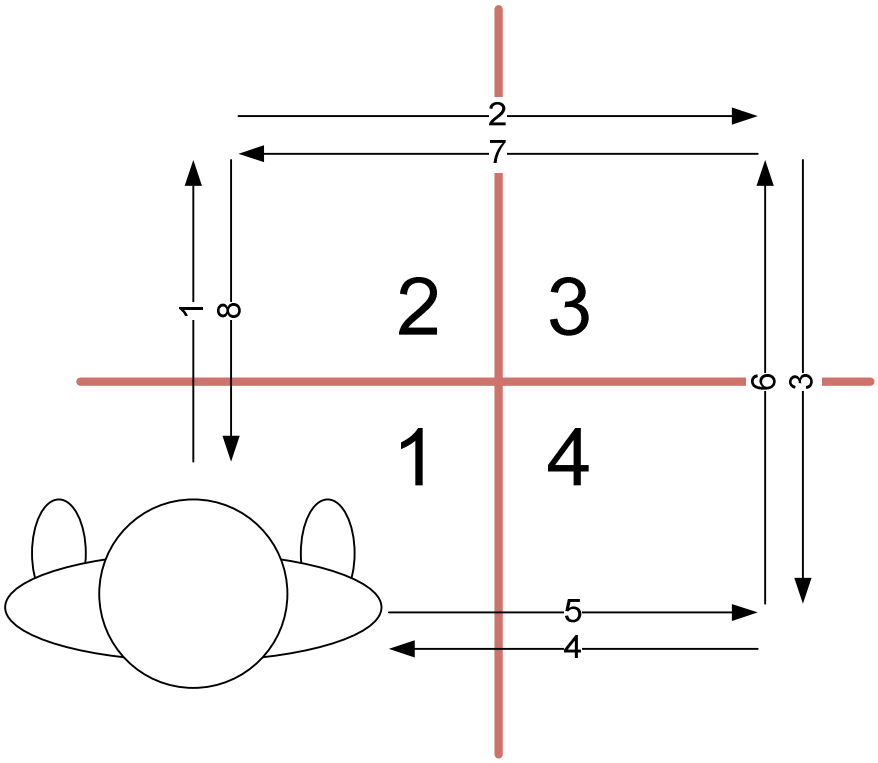


Figure 2.3 - Administration of the FSST. The FSST involves stepping forwards, sideways and backwards. The test subject performs eight steps in the order and direction shown. Adapted from [43].

(n=20, ICC=0.98). The FSST also demonstrated a sensitivity of 89% and specificity of 85% discriminating between multiple fallers and non-multiple fallers, using falls history for the six months prior to the study. In a study of 32 elderly subjects with balance disorders, Whitney *et al.* [44] found the FSST demonstrated a sensitivity of 80% and specificity of 92% in discriminating subjects with 1 or more identified falls risk factors. The authors concluded that the FSST was a reliable, valid and easy to score clinical test requiring minimal equipment. Thus, the FSST is suitable for quick screening for falls risk.

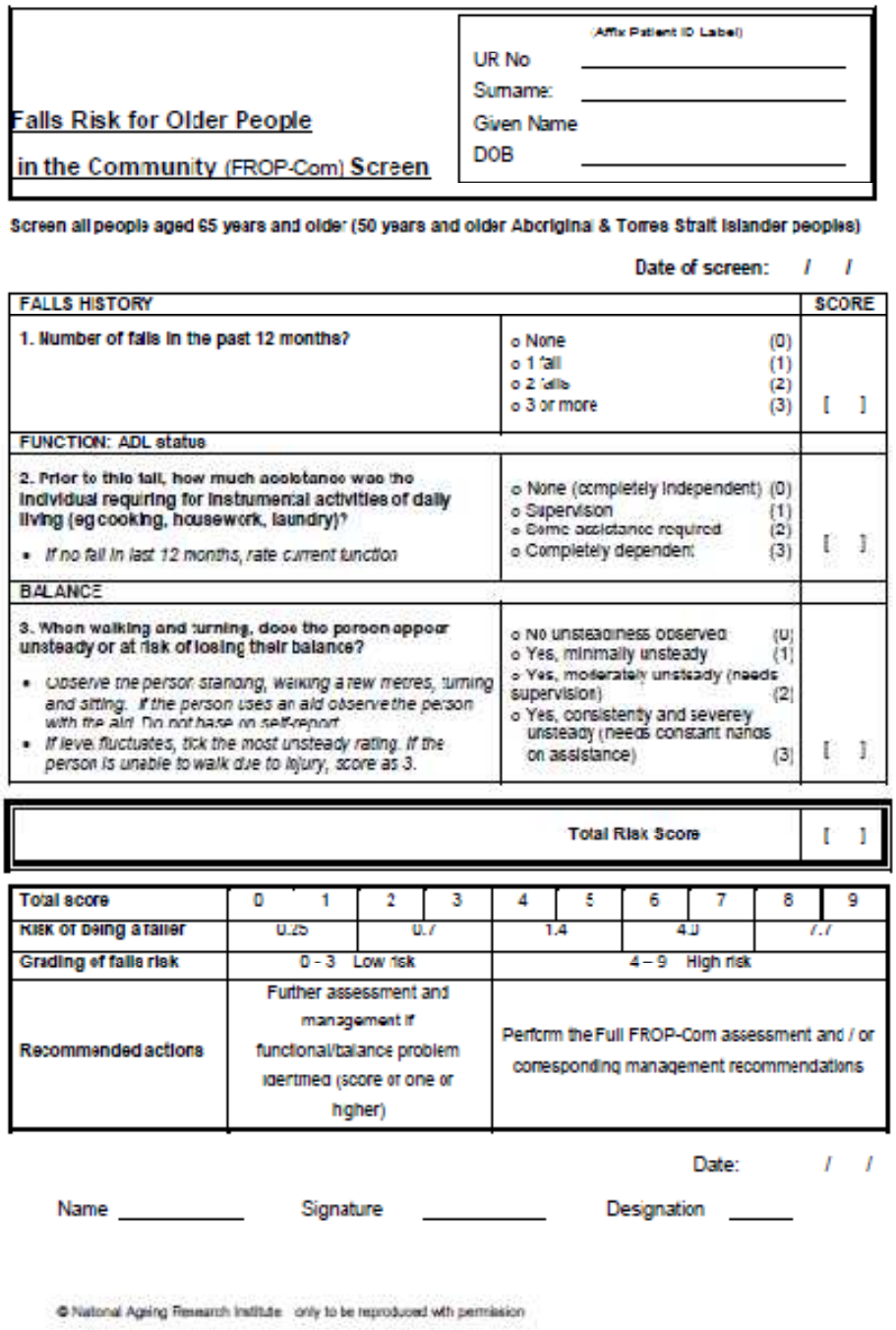
The Floor Transfer Test (FTT) is another functional mobility task that involves transitioning from a standing position to sitting on the floor and returning to a standing position. It was found that 47% of elderly who experienced no injuries were unable to get up and that an inability to get up was associated with increased mortality in the 12 months after the fall [45]. In a study of 50 community-dwelling elderly subjects with a mean age of 72.3(±8.6) years, Murphey *et al.* [46], found that the FFT was one of the two best discriminators between fallers and non-fallers using falls history tracked over the 14 months prior to the study. Other potential discriminators evaluated included the STS5, 5-Step test, 360^{o} turn and 50-ft walk. They found that the FFT had a sensitivity of 64% and specificity of 100% when discriminating between fallers and non-fallers and concluded that the FFT is suitable as a quick screen for falls in the elderly.

In contrast to the functional mobility tests evaluated as a falls risk screen, a number of multifactorial screens have been evaluated. These screens incorporate a number of risk factors for falls when assessing one's risk.

The Falls Risk for Older People in the Community (FROP-com) is one such multifactorial falls risk assessment tool [47-48]. The FROP-com assesses 13 risk factors for falls using 26 questions scored on an ordinal scale (0-3) or dichotomously (0-1). The FROP-com items include falls history, an observation of balance, incontinence, vision deficits, medications, level of activity and cognitive status. In a prospective cohort study of 344 community-dwelling elderly subjects presenting to an emergency department, a screening model was developed using a subset of the 26 questions in the full version of

the FROP-com. The final screening model included falls history, an observation of balance and the need for assistance in performing activities of daily living (ADL). The screen is scored out of 9. An example scoring sheet is shown in Figure 2.4. The history of falls is rated as zero for no falls, 1 for a single fall, 2 for two falls and 3 for three or more falls. The observation of balance is rated out of 3, with 0 for no observable unsteadiness and 3 for marked unsteadiness. Similarly, assistance during ADL is rated out of 3, with 0 scored for total independence and 3 for complete dependence. Falls were prospectively recorded for a period of 12 months following the assessment using FROP-com. A score of more than four had a sensitivity of 70% and specificity of 59.02% in identifying recurrent fallers. The authors concluded that given the FROP-com is quick and easy to apply, the FROP-com could be used to identify elderly at high risk for falls, which provides an approach to administering intervention.

Tromp *et al.* [42], described a Falls Risk Screening Test (FRST) to identify fallers in the community-dwelling elderly. A prospective cohort study, involving 1285 community-dwelling elderly over the age of 65, evaluated 31 factors associated with falls, including: sociodemographic factors; chronic diseases; physiological assessment; functional mobility; falls history; and the fear of falling. Fall events were captured prospectively via falls calendars for a period of 12 months after the clinical evaluation. Two models were developed, one for the identification of fallers and the other for the identification of multiple-fallers. The first model, for the identification of elderly fallers, was derived from falls history, visual impairment, presence of urinary incontinence and the use of benzodiazapenines. The second model, for the identification of recurrent fallers, was



Falls Risk for Older People

in the Community (FROP-Com) Screen

(Affix Patient ID Label)

UR No _____

Surname: _____

Given Name

DOB _____

Screen all people aged 65 years and older (50 years and older Aboriginal & Torres Strait Islander peoples)

Date of screen: / /

FALLS HISTORY		SCORE
1. Number of falls in the past 12 months?	o None (0) o 1 fall (1) o 2 falls (2) o 3 or more (3)	[ ]
FUNCTION: ADL status		
2. Prior to this fall, how much assistance was the individual requiring for instrumental activities of daily living (eg cooking, housework, laundry)? • *If no fall in last 12 months, rate current function*	o None (completely independent) (0) o Supervision (1) o Some assistance required (2) o Completely dependent (3)	[ ]
BALANCE		
3. When walking and turning, does the person appear unsteady or at risk of losing their balance? • *Observe the person standing, walking a few metres, turning and sitting. If the person uses an aid observe the person with the aid. Do not base on self-report* • *If level fluctuates, tick the most unsteady rating. If the person is unable to walk due to injury, score as 3.*	o No unsteadiness observed (0) o Yes, minimally unsteady (1) o Yes, moderately unsteady (needs supervision) (2) o Yes, consistently and severely unsteady (needs constant hands on assistance) (3)	[ ]
	Total Risk Score	[ ]

Total score	0 1	2 3	4 5	6 7	8 9
Risk of being a faller	0.25	0.7	1.4	4.0	7.7
Grading of falls risk	0 - 3 Low risk		4 – 9 High risk		
Recommended actions	Further assessment and management if functional/balance problem identified (score of one or higher)		Perform the Full FROP-Com assessment and / or corresponding management recommendations		

Date: / /

Name _____ Signature _____ Designation _____

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Figure 2.4 - Test result sheet for the FROP-com falls risk screening test, describing the tests and grading of results [47].

derived from falls history, visual impairment, presence of urinary incontinence and functional limitations. Visual impairment was ascertained by self-reported difficulty in recognising a face at a distance of four metres, while functional limitations was identified by the self-reported difficulty in performing two out of the following three functional tasks namely, climbing stairs, use one's own or public transport or cutting their own toenails.

In the case of the second model a score out of 15 is obtained, with previous falls scoring 5 points, visual impairment scoring 4 points and the presence of urinary incontinence and functional limitations scoring 3 points each. The authors found a score of more than 7 or 8 had sensitivities and specificities of (54%, 79%) and (47%, 84%), respectively in identifying multiple fallers. The FRST is quick, requires no equipment and is simple to administer, making it a potentially useful screening tool. The predictive accuracy however, is not very high.

The Elderly Falls Screening Test (EFTS) is a five-item, mulifactorial falls risk screening tool for elderly community-dwelling elderly [49]. The score in the screening test is obtained from a self-reported falls history and an assessment of gait function. This is shown in Figure 2.5. A score of 2 or more classifies the test subject at high risk of falling. 283 subjects were prospectively followed for a period of 12-months after the initial assessment. At baseline, the authors observed that those classified as high risk, were more likely to have fallen in the past 12 months, were more likely to have a number of near falls and were more likely to have suffered an injury from falling. Using the

prospectively recorded falls history, being classified as high risk via the EFTS resulted in 6.23 times the risk of multiple falls. The authors evaluated the validity of the EFTS by comparing the EFTS designations against risk assessment conducted by physician's expert in falls risk. They found that the EFTS, when using a cutoff score of 2, had a sensitivity of 83% and specificity of 69% in identifying those at high risk of falling. The authors concluded that the EFTS is a short, easily administered assessment that has value in identifying those that would benefit from preventative interventions.

Part I – Self-reported fall history
Ask 'How many times in the past year did you fall?'
0-1 falls, score = 0
2+ falls, score = 1
If they fell, ask 'Did you injure yourself?'
No injury, score = 0
Any injury, score = 1
Ask 'How often do you have near falls?'
Never or rarely, score = 0
Occasionally or frequently, score = 1
Part II – Observations on gait patterns
Time the subject walking a distance of 5m at normal pace
If the time taken is less than 10 s, score = 0
If the time taken is more than 10 s, score = 1
Observations about gait
If gait is even, straight and feet are raised with each step, score = 0
If gait is uneven, shuffling, on a wide base, or unsteady, score = 1

Figure 2.5 - Test result sheet for the EFTS describing the tests and grading of results. Adapted from [48].

Stelenhoef *et al.* [50], developed a mulitfactorial falls risk model for the identification of recurrent fallers, in the community-dwelling elderly, suitable for use in general practice. In a prospective cohort study, involving 311 community-dwelling elderly, subjects were assessed over a broad range of factors, including: socio-demographic factors such as age, sex and living-status; falls history; physical health including height, weight, Body Mass Index, hearing and strength; mental health; mobility impairment; and functioning. Subjects were followed for a period of 36 weeks after assessment. Falls were ascertained every 6 weeks. Out of the large number of variables assessed the authors found four variables best discriminated between recurrent fallers and non-fallers, namely abnormal postural sway, two or more falls in the previous year, poor hand grip strength and depression. Using these four variables, the authors constructed a model in which, the probability of being a recurrent faller is presented for each combination of the four risk factors. Subjects were classified as low-risk if 0-1 risk factors are present, moderate risk if 2 risk factors are present and high risk if 3 or more risk factors are present. For men, being high risk, resulted in a predicted probability of falling between 69-90%, while for women, being high risk resulted in a predicted probability of falling between 61-86%. The authors concluded that the model is easy to use and can be used to identify elderly at risk of recurrent falls in a general practice setting. However, use would be dependent on the outcomes of studies that determine the validity and feasibility of the assessment.

Nandy *et al.* [51], developed the Falls Risk Assessment Tool (FRAT), a five-item multifactorial tool used to assess falls in the 6 months after assessment. FRAT assesses risk factors for falls via the responses to four questions on falls history, prescription

medications, medical conditions and balance, as well as a simple test of function, to evaluate falls risk. The questions and grading are shown in Figure 2.6. A score of 3 or more, indicating the presence of at least three risk factors, is used to classify an elderly test subject as high risk. Using prospective falls data for the 6 months subsequent to the assessment, for 345 community-dwelling elderly over the age of 65, a FRAT score of three or more predicted fallers with a positive predictive value (PPV) of 57% and a negative predictive value (NPV) of 86%. The FRAT is quick to administer, taking only a couple of minutes to complete, and requires no equipment, thus making suitable for incorporation into routine assessment in order to potentially identify those who would benefit from intervention.

How many times in the past year did you fall?
0 falls, score = 0
1+ falls, score = 1
How many medications are prescribed to you?
< 4 prescription medications, score = 0
≥ 4 prescription medications, score = 1
Have you had a stroke or do you have Parkinson's disease?
No, score = 0
Yes, score = 1
Do you have problems with balance?
No, score = 0
Yes, score = 1
Inability to rise from a chair without using arms?
No, score = 0
Yes, score = 1

Figure 2.6 - Test result sheet for the FRAT describing the tests and grading of results.

Covinsky *et al.* [52], developed a similar multifactorial falls risk assessment based on the self-reported history of falls, dizziness and balance difficulty, as well as a mobility exam, to discriminate between those at low-risk and high-risk of falls. Mobility was assessed using a small battery of functional tests including, standing up from an armless chair, sitting down into an armless chair, raising feet when walking and being able to turn 180^{o}. Each of the mobility tasks was rated as normal, completed with difficulty or unable to complete. Abnormal mobility was then taken as difficulty in two or more of the mobility tasks or the inability to complete at least one of the tasks. One point was scored for those with a history of falls in the previous 12 months, two points for those with abnormal mobility (as defined above) and two points for a self-reported history of dizziness or balance difficulty. In a prospective cohort study, involving 557 community-dwelling elderly living in a retirement village, a score of three or more was found to have a PPV of 42% and NPV of 84% in predicting falls in the next 12 months. The authors concluded that the index provides a simple method of assessing falls risk in community-dwelling elderly. The assessment requires minimal equipment and is simple to administer.

Pluijm *et al.* [53], developed a risk profile to identify recurrent fallers in the community-dwelling elderly. A large, 3-year prospective cohort study was used. 1365 community-dwelling elderly aged 65 years and over, were assessed on 38 potential predictors at baseline. The predictors included sociodemographic characteristics, chronic diseases and medications use, physical impairments, activity and mobility, psychological factors and life style factors. Of the 38 potential predictor variables, the 9 best discriminators of recurrent fallers, during the 3-year follow-up period, were used to generate a model for

recurrent falls. These included, two or more falls in the previous year, history of dizziness, functional limitations, poor grip strength, low body weight, fear of falling, education level, presence of dogs or cats at home and alcohol use. The model scored elderly out of 30, with a score of 5 or more found to have a sensitivity, specificity, PPV and NPV of 59%, 71.4%, 38.6% and 85.1% respectively, in predicting recurrent fallers within three years of assessment. Given the assessment is predominantly questionnaire-based and requires only a weight scale and dynamometer to perform, the authors found the assessment simple to use and suitable for the identification of recurrent community-dwelling elderly fallers. An interesting outcome of the study is the potential to identify recurrent fallers within three of the assessment. The implication of this is the possibility of administering intervention quite early.

Toba *et al.* [54], developed a simple, self-administrable, questionnaire-based falls risk index, which combines both intrinsic and extrinsic risk factors for falls, to identify fallers from non-fallers. The falls risk index combines falls history, functional ability and medications use, to evaluate falls risk. The falls risk index is shown in Table 2.1. Falls risk is evaluated as a score out of 13. In a study of 2439 community-dwelling elderly, aged 76.3 ± 7.4 years, it was found that a score of 7 or more discriminated between fallers and non-fallers with a sensitivity of 68% and specificity of 71%. The falls risk index is very simple to administer and requires no equipment.

Table 2.1 – Falls Risk Index. Adapted from [54].

Please check the items that belong to you	
☐ I experienced falls in the past 12 months	5 points
☐ My back has become bent	2 points
☐ My walking speed has become slower	2 points
☐ I use a cane	2 points
☐ I take 5 or more different medicines every day	2 points
	Total _____ points

Berg *et al.* [55], developed the Berg Balance Scale (BBS), a performance based measure of balance. The BBS assesses balance via a battery of functional assessment tasks, each of which, are rated out of four, with 0 scored if the subject needs assistance, is unable to complete the task or loses balance, and 4 scored if the subject is able to perform that task well. The BBS has 14 functional assessments and is thus scored out of 56. The functional assessments include the ability to perform sit-to-stand and stand-to-sit transfers, the ability to stand unsupported, and the ability to pick up an object from the floor. The BBS demonstrated excellent inter-rater and intra-rater reliability [55]. The BBS has been used as a screening tool to identify elderly at risk of falling. Various cutoff scores have been described in the literature, to discriminate between non-fallers, fallers, and recurrent fallers.

Lajoie *et al.* [56], in a study of 125 community-dwelling elderly, found that fallers had lower ($P<0.01$) BBS scores than non-fallers and that a cutoff of 46, discriminated between fallers and non-fallers with a sensitivity of 82.5% and a specificity of 93%. Chiu

et al. [57], in a study of 78 community-dwelling elderly, in which falls were tracked for the 6 months prior to assessment, found that a cutoff of 47 using the BBS was able to discriminate between fallers and non-fallers with a sensitivity of 88% and specificity of 77%. It was also found that a cutoff of 38 was able to discriminate between recurrent fallers and non-fallers, with a sensitivity and specificity of 96%.

The BBS is quite easy to administer, requiring only simple equipment. However, given it takes about 15-20 minutes to complete, it may not be very suitable for use in a clinical environment in which a quick assessment of falls risk could easily be incorporated.

Reuben *et al.* [58], developed the Physical Performance Test (PPT) which assesses multiple domains of physical function through observed performance in tasks simulating ADL. The aim was to develop an objective, quantifiable, assessment of physical performance. The PPT assesses the ability to turn 360^{o}, put on and remove a jacket, lift up a book and place it on a shelf, pick up a coin from the floor, walk 50 feet, climb stairs, simulate eating and write. 9-item and 7-item versions were developed. The 7-item version excludes stair climbing. A score from 0-4 are assigned to each item based on the ability to complete the task or the time taken to complete the task. The PPT has demonstrated good inter-rater reliability [58]. The PPT has been used to discriminate between non-fallers, fallers and recurrent fallers in community-dwelling elderly.

VanSwearingen *et al.* [59], found the PPT to be a clinically useful measure for the screening of elderly at risk of recurrent falls in a study of 84 community-dwelling elderly,

aged 75.5 ± 7.33 years. A cutoff of 15/28, using the 7-item version of the PPT, was found to discriminate between non-fallers and recurrent fallers with a sensitivity and specificity of 79.3% and 71.0%, respectively. Delbaere *et al.* [60], in a large scale prospective study of 263 community-dwelling elderly, with a mean age of 72 years, found a score of 25 or less, best predicted future falls. The odds ratio (OR) for future falls, with a score 25 or less, was found to be OR=4.14, P<0.001.

Hernandez *et al.* [61], developed the Fullerton Advanced Balance scale (FAB), designed to assess static and dynamic balance in the elderly. The FAB is a 10-item assessment, with each item scored from 0-4, representing poor to excellent performance. The FAB assesses the ability to stand with feet together with eyes closed, reaching forward to pick up an object, turning in a circle, stepping over a bench, tandem walking, standing on one leg, standing on a compliant surface with eyes closed, jumping, walking while turning your head and the ability to recover from an unexpected loss of balance [62]. The FAB has demonstrated excellent inter-rater and intra-rater reliability [61]. A score of 25 or less was found to discriminate between fallers and non-fallers, using a retrospective falls history, in a study of 192 independently functioning older adults, aged 77.0 ± 6.5 years, with a sensitivity and specificity of 74.6% and 52.6% respectively. The FAB takes about 10-12 minutes to complete and requires 9 pieces of equipment to administer, including a stop watch, metronome, masking tape, foam pads and a yardstick, all of which are relatively inexpensive.

Powel *et al.* [63], developed the Activities-specific Balance Confidence scale (ABC), a 16-item self-administered questionnaire which asks subjects questions about how confident they are that they will not lose balance or become unsteady when performing a number of typical daily activities such as, walking around the house, walking up and down stairs and getting into and out of a car. The subject rates their confidence from 0% to 100% representing no confidence to complete confidence, respectively. The average percentage confidence for the 16 items forms the ABC score. It was found that fallers had a lower mean score on the ABC when compared to non-fallers. Lajoie *et al.* [56], reported a cutoff of 67% was able to correctly classify fallers from non-fallers, with a sensitivity and specificity of 84.4% and 87.5% respectively, in a study of 125 community-dwelling elderly. The ABC is quick and simple to administer, requiring no equipment. Thus, the ABC is suitable for use in busy clinical settings to identify elderly at increased risk of falls.

Tinetti *et al.* [64], developed the Falls Efficacy Scale (FES), a 10-item questionnaire designed to measure fear of falling in the elderly. The FES evaluates the extent to which fear of falling affects functional decline in the elderly and is based on activities essential for independent living as determined by therapists, nurses and physicians [64]. The questionnaire asks questions about the subject's ability to get dressed, get on and off the toilet, take a bath or shower, get onto and off of a chair, get into and out of bed and walk around the house. Each item is rated out of 10, with higher scores relating to lower perceived self-efficacy or confidence in performing a given task. The ability of the FES

to discriminate between non-fallers, fallers and recurrent fallers has been evaluated in a number of studies.

Tromp *et al.* [42], assessed a modified version of the FES in which the 10 items were rated out of 3 instead of 10, with 0 scored for no confidence and 3 for complete confidence. In a prospective study involving 1285 community-dwelling elderly over the age of 65, it was found the lower FES scores were associated with increased odds of recurrent falls (OR = 2.0) using prospectively recorded falls history.

In another study using the FES, Cumming *et al.* [65], in a prospective study of 528 elderly subjects, in which falls were monitored for 12 months post-assessment, found that a score of 75 or less on the FES significantly increased the relative risk of falling during the 12 month followup period (RR = 2.09, 95%CI = [1.31, 3.33]).

In contrast to the models described by other researchers, Stel *et al.* [66] developed a classification tree for the prediction of recurrent fallers in the community-dwelling elderly in which, the terminating nodes of the classification tree provide the risk of falling for various combinations of risk factors. The classification tree is multifactorial in nature, using a variety of falls risk factors in predict the risk of falling including, sociodemographic characteristics, chronic diseases and medications use, physical impairments, activity and mobility, psychological factors and life style factors. The classification tree, shown in Figure 2.7, was derived from the prospectively recorded falls data, over a three year follow-up period, in 1365 community-dwelling elderly over the

age of 65. The circles represent groups of elderly with a particular combination of risk factors. The squares contain the percentage of those, from the parent group, when considering an additional risk factor that became recurrent fallers in the study. Consider for example the group designated 1, which represents elderly with a history of two or more falls in the past year and have a functional limitation score of less than 2. Of the elderly who fall into group 1, those with self-reported history of dizziness have a 68% chance of becoming recurrent fallers, while those with no dizziness have a 30% chance of becoming recurrent fallers. The most interesting aspect of the classification tree-based approach is the ability to show how different combinations of risk factors contribute to ones overall risk of becoming a recurrent faller. This approach provides increased granularity in identifying recurrent fallers for a given set of risk factors, thus ensuring those that would potentially benefit from intervention receive it. Unfortunately, the model has not been validated on an additional cohort of elderly subjects. Nevertheless, it has the potential for use as a quick screen for identifying fallers.

More recently, Leclerc *et al.* [67], used a similar classification tree-based approach for the identification of recurrent fallers in the community-dwelling elderly. They used a Classification and Regression Tree (CART) model using falls risk data from 868 community-dwelling elderly prospectively tracked for falls in the 6 months following the assessment. In contrast to the model developed by Stel *et al.* [66], Leclerc and colleagues used only four predictors in the classification of recurrent fallers. The classification tree, shown in Figure 2.8, used falls history in the past three months, score on the Berg Balance Scale (BBS) [55], and type of housing and alcohol consumption to determine the

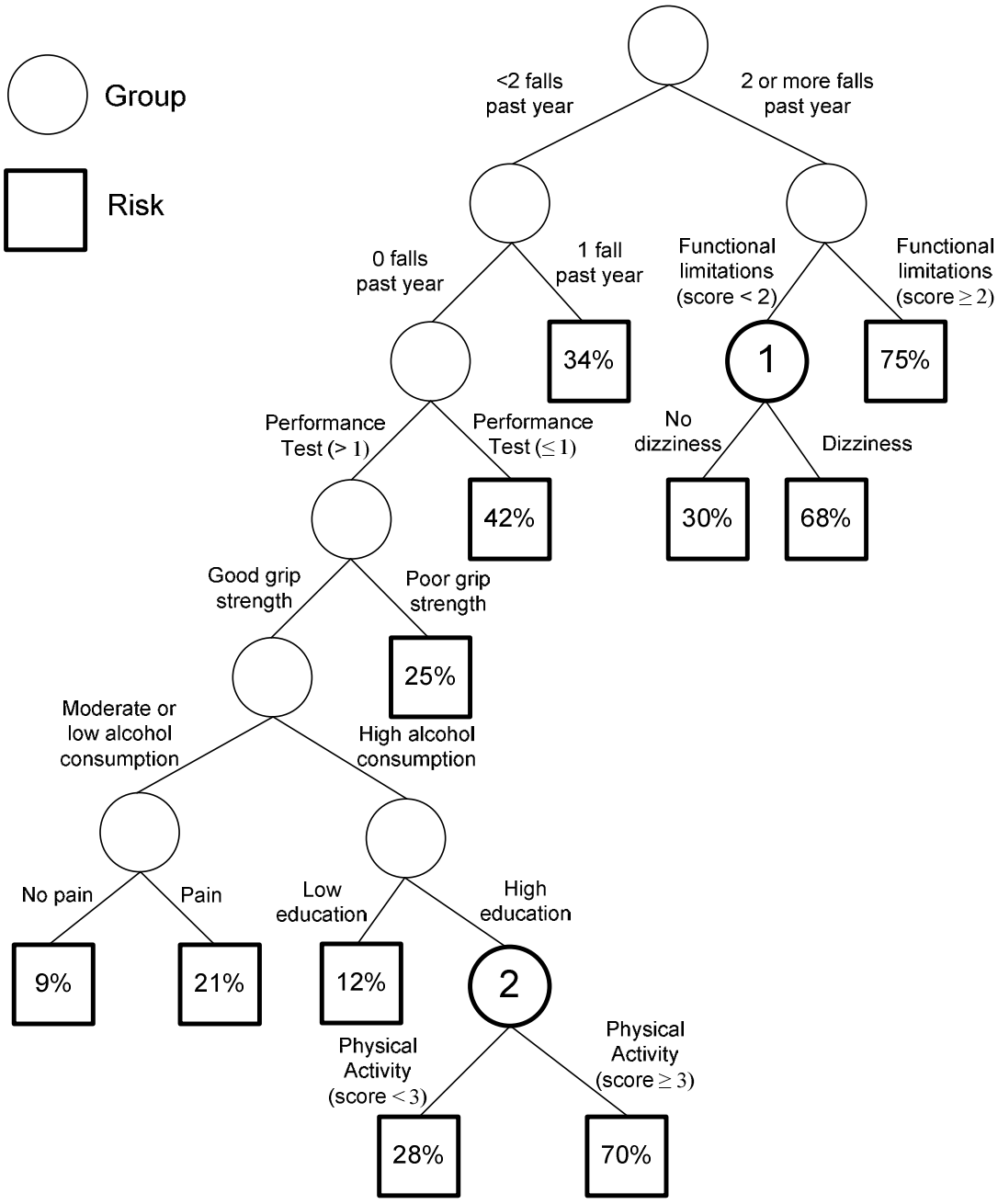


Figure 2.7 - Classification tree for the identification of recurrent fallers. The classification tree presents the probability of becoming a recurrent faller using between 2-6 falls risk predictors. Adapted from [65].

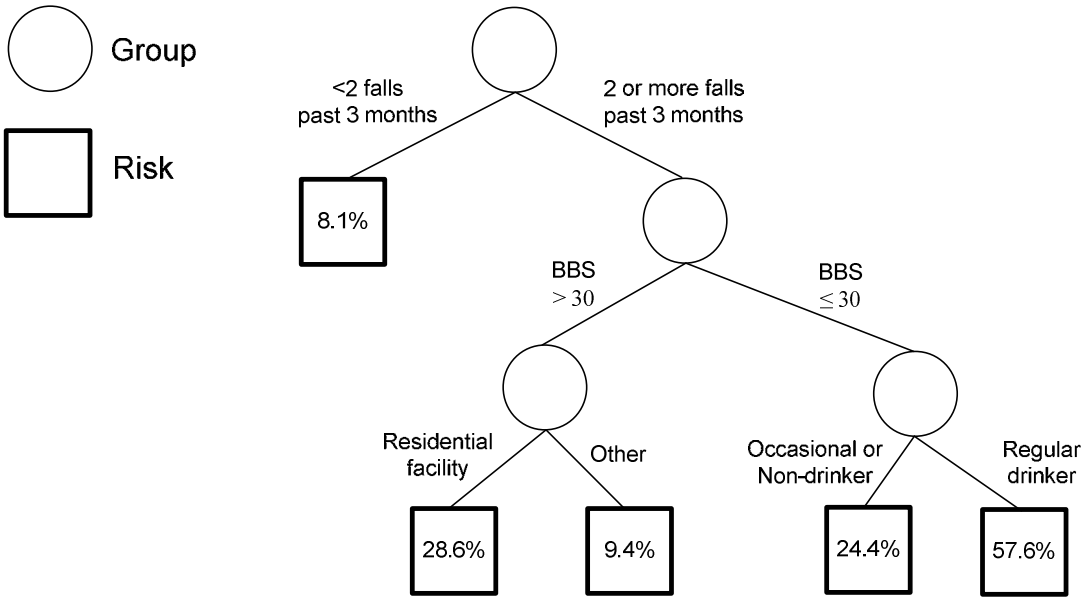


Figure 2.8 - Classification tree for the identification of recurrent fallers. The classification tree presents the probability of becoming a recurrent faller using between 1-3 falls risk predictors. Adapted from [66].

risk of becoming a recurrent faller. From the classification tree, it can be seen that an elderly test subject with a history of two or more falls in the past three months, a score of less than 30 on the BBS and who is a regular drinker has a 57.6% chance of becoming a recurrent faller. In this study, it represented a relative risk 5.1 times higher compared with the total sample population.

2.3.2 Comprehensive falls risk assessment tools

Falls risk screening tools are simple tools for the identification of elderly at increased risk of falling and do not necessarily provide much information about particular physiological risk factors. In contrast, falls risk assessment tools not only evaluate falls risk but assess a wide range of physiological and functional factors associated with falls risk to provide a detailed evaluation of the underlying risk factors contributing to one's risk of falling [36].

Russel *et al.* [47], developed and evaluated the FROP-com assessment tool, a comprehensive version of the screening tool [48] described in the preceding section. The FROP-com is a comprehensive falls risk assessment tool covering a broad range of falls risk factors via a set of 26 questions. The score obtained using the FROP-com directly relates to falls risk. The broad range of risk factors assessed, were selected to enable the FROP-com to be used with multifactorial intervention programs. The FROP-com covers risk factors including, falls history, medications, medical conditions, sensory function, cognitive status, continence, functional ability including ADL, balance and gait, as well as environmental risk factors. The FROP-com is scored out of 60. Falls risk increases with increasing FROP-com scores. Scores between 0-18 are indicative of mild to moderate falls risk and scores above 18 indicative of high falls risk. The FROP-com demonstrated excellent intra-rater and inter-rater reliability. In a prospective study of 344 community-dwelling elderly, a score of 18 or more had the best sensitivity and specificity in identifying future fallers, using the prospective falls history, of 71.3% and 56.1%, respectively. Interestingly, the FROP-com requires no equipment, making it quite simple

to administer. The FROP-com was found to take about 10-15 minutes to administer. The FROP-com is one of a number of falls risk assessment tools recommended in the ACSQHC guidelines for preventing falls [36].

Tiedemann *et al.* [40, 68], developed the Quickscreen, a comprehensive multifactorial assessment of falls risk recommended in the ACSQHC guidelines for preventing falls [36]. The Quickscreen provides a risk of falling and provides details of particular risk factors contributing to falls risk. The Quickscreen assesses eight risk factors for falls using falls history, medications, vision, peripheral sensation and strength, balance and reaction time using a simple visual acuity test, tactile sensitivity assessment, the near-tandem standing balance test (NTSB), AST and STS5. In a large scale prospective study, involving 1126 community-dwelling elderly, the relative risk (RR) for future falls was evaluated for the number of risk factors affecting an individual. 0-1 identified risk factors results in a RR = 1, 2-3 identified risk factors results in a RR = 1.7, 4 identified risk factors results in a RR = 4.7 and 5 or more identified risk factors results in a RR = 8.6. A cutoff of 4 or more risk factors was found to discriminate between multiple fallers and non-multiple fallers with a sensitivity of 76% and specificity of 60% [68]. The functional assessments used in the Quickscreen have demonstrated good reliability and validity [40]. The Quickscreen takes about 10 minutes to complete and requires a few, relatively simple, pieces of equipment.

Lord *et al.* [17], developed the Physiological Profile Assessment (PPA), a comprehensive, mulifactorial, validated falls risk assessment tool in which the falls risk

score is derived from quantifiable physiological measures. The PPA evaluated physiological function via tests that were simple to administer, had short administration times, were feasible for the elderly to perform, valid and reliable, low-tech, portable and quantitative. The PPA has two versions, both of which provide the same falls risk score, in which the longer version provides greater insight into one's physiological impairments through a more comprehensive assessment of function. The PPA assesses vision, vestibular function, peripheral sensation, muscle strength, balance and reaction time. The PPA has demonstrated accuracies of between 75-79% in predicting multiple fallers in a number of prospective studies [20, 24, 69]. The short-form of the PPA, which assesses vision, peripheral sensation, lower-extremity strength, reaction time and body sway, was found to take about 15 minutes to administer. The long-form on the other hand, takes about 45 minutes to administer. An interesting aspect of the PPA is that it generates a graph showing the subjects overall falls risk score within the ranges defined for low risk, normal risk and high risk, as well as a chart showing the normalised performance on each of the assessment tasks with respect to the elderly population and recommendations for the improvement of functional performance with respect to identified impairments.

2.3.3 Summary of falls screening and assessment tools

The screening tools described highlight the incredible variation in approach, to developing screening tools to identify elderly at risk of falls. Screens vary in outcome, for the identification of fallers or recurrent fallers, in design, questionnaires, physiological assessment and combinations of them have all been tried. There is no gold standard

screening methodology. Quite a few of the screening tools used rely upon the subjective evaluation of functional ability. It is readily acknowledged that simple screening tools that can be used in time critical clinical settings are needed. To this end, ambulatory assessment of falls risk, using simple wearable monitors, have the potential to deliver fast, objective and deterministic falls risk evaluations.

2.4 Interventions for falls

Epidemiological studies have revealed many risk factors for falls in the elderly. Many of the identified risk factors are known to be amenable. Given this, interventions have been developed to prevent falls on the basis of identified risk factors. Three basic types of intervention have been trialed [70]. Single interventions, in which one major category of intervention is applied to all participants, have been evaluated. Multiple-interventions, which combine two or more major categories of interventions, as well as, multifactorial interventions, which are tailored inverventions in which participants receive more than one category of intervention but in varying categories and amounts based on individual assessment, have been investigated.

Major intervention categories include exercise interventions, such as balance and strength training, medication interventions such as medication modifications, surgical interventions such as cataract surgery, psychological interventions such as behavioural

therapy, environmental interventions such as home hazard reduction, and educational interventions, providing knowledge about falls and falls prevention [70].

The affect of intervention on the rate of falls, risk of falls and injury reduction, have been evaluated in large number of randomised control studies. Single, multiple and multifactorial interventions have all shown reductions in the rate and risk of falls. In particular, exercise interventions, such as group exercise classes and home-based exercise programmes, have been shown to lead to significant reduction in the rate and risk of falls [70-72]. Taking calcitriol and the gradual withdrawal of psychotropic medications have proven effective medication interventions, with a significant reduction in the rate of falls [70, 73-74]. Cardiac pacing in fallers with cardioinhibitory carotid sinus hypersensitivity as well as cataract surgery has been shown to be useful surgical interventions [70, 75-76].

In particular, Barnett *et al.* [71] achieved a 40% reduction in the rate of falls in participants attending a community-based exercise programme, in randomised controlled study of 163 elderly over the age of 65. Day *et al.* [72] found a 6.9% reduction in the rate of falls, in participants receiving weekly strength and balance training, in a randomised controlled study of 1090 community-dwelling elderly.

Harwood *et al.* [75] found a 34% reduction in the rate of falls, for those who had expedited cataract surgery, compared with a control group who had a routine wait for surgery, in a randomised control study of 306 elderly subjects over the age of 70.

In terms of multiple interventions, Campbell *et al.* [77] found a significant reduction in the number of falls in those who adhered to a multiple-component intervention combining home safety assessment and modification and an exercise programme providing muscle strengthening and balance training, in a randomised control study of 391 elderly over the age of 75. Similarly, Day *et al.* [72] found a 14% reduction in the rate of falls in those provided with an exercise, vision, and home hazard management multiple intervention, in a randomised control study of 1090 community-dwelling elderly.

Davison *et al.* [78] trialed a multifactorial intervention. A comprehensive assessment of vision, cardiovascular function, medications use, gait and balance as well as environmental hazards, was used to assign interventions to those in an intervention group of a randomised control study of 313 elderly over the age of 65. It was found there was a 36% reduction in the rate of falls in the intervention group.

These studies show that targeted interventions, applied on the basis of risk factor assessment, lead to a reduction in the rate of falls and the risk of falls in the elderly. Thus, accurate tools identifying those at risk of falls and evaluating risk factors for falls can aid in the management of falls in the elderly community.

2.5 Ambulatory monitoring

2.5.1 Introduction

Significant advancement over the last 10 to 15 years has been made in sensor technology and embedded systems. Miniature sensors measuring accelerations, rotation, magnetic fields and barometric pressure for example, coupled with powerful, low power, embedded systems enabled the development of wearable ambulatory monitors to objectively evaluate human movement and functional ability.

Ambulatory monitors developed, vary in placement, number, type and application. Ambulatory monitors attached to various locations on the head, trunk, arms, legs and feet have been evaluated. Single device systems, placing the device on a single location on the body, to multiple device systems, placing sensors on multiple locations on the body have been investigated. These devices have typically been made up of accelerometers, gyroscopes, magnetometers, barometric sensors, or combinations of them. Ambulatory monitors for physical activity monitoring [79-81], the evaluation of position and orientation of body segments [82-85], activity classification [86-88], mobility assessment [101], such as assessments of balance [110-114], gait and strength [120, 123-128], as well as falls detection [94-100], have been evaluated. Systems designed for clinical use and unsupervised monitoring have been developed [86-88].

In terms of applications for the monitoring of the elderly, the potential of ambulatory monitors to detect falls, evaluate risk factors for falls, and evaluate falls risk in the elderly has been frequently discussed [89-93]. It is envisaged that simple ambulatory monitors have the capability of providing quick screens to identify elderly prone to falling, comprehensive falls risk evaluation identifying amenable risk factors for falls, and aiding in the delivery of appropriate interventions. The potential value of these monitors in enhancing the management of falls in the elderly not only benefits the individual but will enable the better management of limited healthcare resources.

The following sections provide an overview of a selection of related wearable devices discussed in the literature that have been applied to the elderly, for the purposes of, real time falls detection, mobility and functional ability assessment and falls risk evaluation.

2.5.2 Ambulatory monitoring of elderly subjects

2.5.2.1 Falls detection

Numerous wearable monitors for the detection of falls have been investigated. Personal alarm systems readily used, rely upon the user to initiate emergency response by pressing a button on a body worn trigger in the event of a fall. While simple in design, they are of limited use if the subject is unable to press the button if injured or unconscious. Wearable monitors able to automatically detect falls in real time enable prompt emergency response

to be provided. The acceptance of such devices, hinges heavily on the ability of the device to identify falls from all other events. The sensitivity of devices developed is typically evaluated in simulated falls using young volunteers and anthropometric mannequins. The specificity is determined by evaluating detection algorithms during the recording of typical daily activities in both young and old subjects.

Doughty *et al.* [94] trialed a fall detector placed on the sternum, waist, wrist and ankle via simulated falls using a mannequin. The fall detector was designed to measure shock and orientation. Falls were simulated in multiple directions. It was found that the chest and waist were the most sensitive, and most feasible, locations for the detection of falls with their device. Surveying 100 elderly subjects, Doughty *et al.* reported 83% of elderly subjects found their waist-mounted prototype comfortable to wear. However, no testing of the falls detection algorithm performance, using young or elderly volunteers performing normal activities or falls was reported.

Lindemann *et al.* [95] conducted a pilot study on an accelerometer-based fall detector, worn on the ear like a hearing aid, to discriminate between normal activities and fall events. A rule-based algorithm was empirically derived that used the magnitude of measured accelerations and an estimation of velocity to classify falls. Performance was evaluated using a single young volunteer who performed simulated falls and daily living activities. Additionally, the system was trialed on an 83 year old volunteer who wore the sensor for a day. It was found that the algorithm could reliably discriminate between

normal activities and fall events. Only a single false positive was detected when the user tapped the monitor with their hands.

Bourke *et al.* [96] investigated the performance of tri-axial accelerometer based falls detectors, attached to the trunk and thigh, to detect falls and discriminate between typical daily activities. Simulated falls were conducted in a variety of directions using 10 young volunteers. Thresholds from the acceleration data were empirically determined from the simulated falls data to classify falls. In addition, 10 community-dwelling elderly, aged between 70-83 years of age, were used to collect samples of typical daily activities, including getting into and out of bed, postural transitions, getting into and out of a car and walking. The authors reported a single threshold for trunk accelerations, above which all simulated falls were correctly classified, and all activities performed by the elderly volunteers did not exceed. Thus, a sensitivity and specificity of 100% was obtained for the trunk mounted fall detector.

In a similar investigation, Bourke and Lyons [97] evaluated a trunk-mounted fall detector using a bi-axial gyroscope to measure rotations of the trunk. Simulated falls and normal daily activities were evaluated in 10 young and 10 elderly volunteers, respectively. Thresholds were found for angular velocity, angular acceleration and angular displacement that could be used to distinguish between normal activities and falls with 100% accuracy.

Kangas *et al.* [98] evaluated a number of algorithms for the detection of falls using a tri-axial accelerometer-based falls detector attached to the head, wrist and waist. Simulated falls in the forwards, backwards and lateral directions, as well as normal activities such as walking, stair climbing and picking up objects from the floor were evaluated in three healthy volunteers. The best performing algorithms were found to be for the devices attached to the head or waist, achieving sensitivities of 98% and 97% respectively, in classifying falls. The algorithms tested, achieved a maximum sensitivity of 71% for the device attached to the wrist. Taking into account usability and acceptance, Kangas *et al.* [98] suggested a waist-mounted device may be the optimal location for a wearable falls detector. To further evaluate the waist-mounted device, Kangas *et al.* [99] conducted a pilot study, in which 20 middle-aged volunteers simulated falls representing those likely to occur as a result of syncope, tripping, slipping, falling from a chair and rolling out of bed. The 20 middle-aged volunteers as well as 21 elderly volunteers, aged between 58-98 years of age, were used to obtain recording of normal activities such as, sitting down, standing up, picking up objects from the floor, getting into and out of a bed and walking. A sensitivity of 97.5% was achieved in identifying falls with a specificity of 100% in discriminating between falls and normal activities.

Bianchi *et al.* [100] investigated the performance of a waist-mounted falls detector, combing a tri-axial accelerometer and barometric pressure sensor, to discriminate between normal activities and falls. The barometric pressure sensor enables changes in altitude to be detected independently of acceleration, which may help classify low-impact falls. An algorithm, combining estimates of peak acceleration, energy expenditure,

postural orientation and differential pressure was derived to classify falls. The addition of a barometric pressure sensor was shown to enhance the performance of the fall detector, especially in cases where the impact from a fall was small. An overall accuracy of 97.1% was achieved, with a sensitivity and specificity of 97.8% and 96.7% respectively, in classifying falls.

These studies show that wearable falls detectors, evaluating movement, have the potential to reliably detect falls. Such devices provide an increased level of comfort and security to independently living elderly, by ensuring assistance is called when needed. This comfort helps provide an overall better quality of life for the elderly.

2.5.2.2 Functional and mobility assessment

Functional and mobility assessment in the elderly is extensively described in the literature, with quite a few ambulatory monitors evaluated to assess daily activities, postural stability, functional assessment tasks and gait in the elderly. Unsurprisingly, the systems developed vary considerably in approach and outcome. This subsection looks to provide an overview of the work done in functional and mobility assessment in the elderly using wearable devices.

A number of studies have focused on the free-living classification of movement and posture in the elderly. Postures, such as sitting, standing and lying, postural transitions such as, sit-to-stand and stand-to-sit transfers, as well as dynamic movements like walking have been regularly assessed. Longitudinal monitoring of free-living activities are expected to yield parameters relating to the amount, type and frequency of activities that can be used to draw inference about the health status and quality of life of the user.

Najafi *et al.* [101], developed an ambulatory monitor for the classification of physical activity in the elderly using a wearable monitor attached to the chest, which characterises movement in terms of angular velocity and acceleration using a pair of uni-axial accelerometers and a uni-axial gyroscope. The system was evaluated in a study of 40 elderly volunteers, including community-dwelling and hospitalised elderly. In the first part of the study, 11 community-dwelling elderly performed known sequences of movements including sitting, standing, lying, postural transitions such as sit-to-stand and stand-to-sit transitions as well as walking, performed on a variety of chair types. Video recordings of the movements were made and used to evaluate the performance of the classification algorithms. Sit-to-stand transitions, stand-to-sit transitions, lying, and walking were detected with a sensitivity and specificity of (93%, 82%), (82%, 94%), (100%, 100%) and (96%, 95%) respectively. In the second part of the study, classification of lying position was evaluated in 24 hospitalised elderly, who were asked to lie in varying positions as well as perform transfers out of bed. Classification of lying sub-states, back, left side and right side, as well as lying transfers were classified with a sensitivity of 100% and specificity of 100% in each case. The last part of the study

involved evaluating the classification algorithms in a free-living situation, in which, 9 elderly subjects were monitored for a period of up to 1 hour during which time an observer recorded the subjects actual posture and movement. Sensitivities and specificities of (90.2%, 93.4%), (92.2%, 92.1%), (92.2%, 91.2%) and (98.4%, 99.7%) for the classification algorithms were detected for sitting, standing, walking and lying, respectively for free-living classification. This study demonstrated the ability to accurately monitor activity in elderly populations in a free-living context, a precondition for effective longitudinal ambulatory monitoring.

Mathie *et al.* [102-104], developed a waist-mounted tri-axial accelerometer based wearable ambulatory monitor for the classification of posture, movement and falls in the elderly [105]. The system uses simple heuristic algorithms to classify movement and posture using an estimate of energy expenditure and an estimate of orientation. Activity and rest are discriminated by the amount of energy expended. Estimates of orientation are used to further discriminate rest and activity into posture and movement classifications, including sitting, standing, lying, walking and falling. The overall accuracy of the system in classifying postures, postural transitions and movements was shown to have a sensitivity and specificity of 97.7% and 98.7% respectively [102]. The system was evaluated in a pilot study of long term monitoring of unsupervised movements, involving 6 healthy elderly subjects aged between 80-86 years, who were monitored for a period between 2-3 months. Subjects wore the monitor from the time they wake up until they go to sleep. They were required to perform a set of controlled movements, called the directed routine, each morning, after which the subjects continued to wear the device as

they went about their daily lives. The directed routine involved performing a set of typical movement tasks involving a number of postures, postural transitions and walking. A number of parameters were extracted from the directed routine data, including an estimate of energy expenditure, postural sway and postural transition durations. Over the duration of the study, no trends were found in the extracted parameters in any of the subjects. From the free-movement data, a mild correlation was found between the weekly estimated energy expenditure and the COOP/WONCA scores [106], which are a measure of the health status of the subjects. User perception of the ambulatory monitoring system was evaluated. All the subjects were initially nervous about using the system for fear of damaging the device. All subjects ultimately found the wearable device comfortable and easy to use. Overall, Mathie *et al.* found using a single waist-mounted ambulatory monitor suitable for unsupervised home monitoring of elderly subjects. The study shows the utility of parameters extracted from free living movement data to be mapped to a measure of health status and provided a means of controlling movements in an unsupervised environment by way of the directed routine.

Allen *et al.* [107], developed a Gaussian Mixture Model (GMM) for the classification of postures and movements during a directed routine of movements including sitting, standing, lying and walking, using a single waist-mounted tri-axial accelerometer. The GMM was trained using features extracted from estimates of the gravitational acceleration component and body acceleration component of the raw accelerations measured at the waist. The gravitational and body acceleration samples, as well as an estimate of energy expenditure and delta coefficients extracted from both components of

the acceleration signal, which describe temporal properties of the acceleration components, were taken as features. The GMM had an overall accuracy of 91.3% in classifying the directed routine movements and postures. The GMM provides a useful means of verifying a directed routine of movements contains the desired set of movements. This is important as parameters extracted from the movements data are used make clinical inferences and thus it is important to know parameters were extracted from reliable movement data.

Fleury *et al.* [108] developed a wearable device, attached to the chest, to classify postural transitions and walking for the elderly. The wearable device was made up of a tri-axial accelerometer and tri-axial magnetometer. A wavelet based pattern recognition algorithm processed measured accelerations and magnetic field data to classify sit-to-stand, stand-to-sit, stand-to-lying and lying-to-stand postural transitions, as well as periods of walking. The algorithm was evaluated in a cohort of 15 young subjects who performed a series of movements in a custom-built smart home. The algorithm was found to have an overall accuracy of 70% in identifying the desired postural transitions and walking. The wearable device was incorporated into a smart home, fitted with a number of passive sensors, to classify more generic daily activities assessed in a number of activity scales used to evaluate dependence and need for institutionalisation in the elderly [109]. When combined with passive sensory information from microphones, passive infrared sensors and door switches, the system was able to detect daily activities relating to sleeping, preparing meals, dressing, resting, going to the toilet and communicating with an overall accuracy of 86%. This study highlights the utility of wearable sensors to supplement

passive sensors in classifying more generic daily activities via a fusion of sensory information.

Postural stability is an important risk factor for falls, with a number of assessments incorporating assessments of balance into the overall assessment of falls risk in the elderly. Clinical measures of balance by way of sway meters or force plates are not very portable and often quite expensive. A number of wearable devices have been constructed to measure postural stability indirectly and provide surrogate measures of balance that are more portable and inexpensive.

Kamen *et al.* [110], described an accelerometry-based wearable monitor for the evaluation of postural stability in terms of body sway. A wearable device, based on a uni-axial accelerometer, was attached to the back at S2 (second sacral vertebrae) which is approximately at the level of the posterior superior iliac spine. Sway amplitude, calculated from the root-mean-squared (RMS) acceleration during the balance test, and sway frequency, estimated from a Fast Fourier Transform of the acceleration sample, were used as proxy measures for body sway. The measures of body sway were evaluated in 10 young subjects, aged 18-32 years, and 10 elderly subjects, aged 69-86 years. Subjects performed tests of balance by standing as still as possible on firm and compliant surfaces for 20 seconds. Tests were performed with eyes firstly opened and then closed. Sway amplitude was able to discriminate between young and elderly subjects, particularly on tests on a compliant surface with eyes closed. Older subjects exhibited

greater sway amplitudes than younger subjects. Given balance is an established risk factor for falls Kamen *et al.* anticipated the system's utility in identifying elderly fallers. The measures of sway were not compared against standard clinical measures. Nevertheless, the study illustrated potential of simple wearable devices to provide measures of balance normally obtained via more complex instrumentation.

Mayagoita *et al.* [111], used a tri-axial accelerometer attached to the back to evaluate standing balance in terms of body sway estimates. Detected accelerations were used to project the movement onto a 2-dimensional plane, at ground level, from which a number of parameters, analogous to force plate measurements, were estimated. The projected path is similar to the sway path obtained by way of a sway meter. Parameters extracted from the projected path include the total mediolateral displacement, total anteroposterior displacement, average sway speed, sway frequency and mean radius. Simultaneous measurements using force plate and accelerometry were taken during testing of standing balance on firm and compliant surfaces with eyes open and closed. It was found that the parameters evaluated via accelerometry measures of standing balance, discriminated between the four test conditions as well as the force plate measures. A significant result showing accelerometry measures of balance have the potential to be as sensitive as force plate measures.

Moe-Nilssen *et al.* [112] developed a wearable monitor to evaluate body sway via a tri-axial accelerometer based device measuring trunk sway at the level of L3 (third lumbar

vertebrae), which is taken as an approximation of the body's centre of mass while standing. Body sway was evaluated in a cohort of 86 subjects, 36 community-dwelling elderly aged between 66-79 years of age, and 50 young subjects aged between 20-41 years of age. Sway was assessed in 30 second trials of standing balance on firm and compliant surfaces with eyes open and closed. The raw accelerations measured were conditioned to remove the gravitational component and drift, with the resultant signal used to evaluate the RMS value for accelerations in the mediolateral and anteroposterior planes. These RMS values form the approximations of body sway. The RMS values were sensitive to the different test conditions and were able to discriminate between young and elderly subjects.

Allum *et al.* [113], evaluated a system, measuring trunk sway, to assess postural stability and differentiate between normal subjects and those with balance disorders. Trunk sway measures were assessed using a wearable device attached to the lower back and measuring angular velocities of the trunk during sway. 15 subjects with acute unilateral vestibular loss (UVL) and 88 normal health subjects with no balance deficits were assessed on a battery of balance tests including, one-legged stance tests, two-legged stance tests and gait tasks. Allum *et al.* showed the simple parameters, extracted from angular velocity measurement of trunk sway, were able to correctly classify normal and UVL subjects with an accuracy of 96.6% and 93.3%, respectively. Allum *et al.* [114] discussed the utility of trunk sway measures to identify fallers and prevent falls in terms of balance rehabilitation via a audio-feedback device. Given balance is an independent risk factor for falls, identifying those with balance deficits may aid in the identification of

elderly fallers. Being able to identify particular balance disorders, as was shown possible in [113], should enable more specific interventions to be applied. Additionally, Allum *et al.* discussed the idea of providing an audio-feedback signal to a wearer, when a subject sways more than a set threshold. The greater the sway the louder the feedback signal. In this way an artificial sense of balance can be provided to those at risk of falling and in particular those with balance deficits. This highlights the utility of miniaturised wearable devices measuring postural stability.

Functional ability has been evaluated in simple mobility tests including the STS test and TUGT. These tests have been used to assess falls risk and serve as means to indirectly assess muscle strength and balance (see **Section** 2.3.1). A number of studies using wearable devices have been used to assess STS and TUGT, to not only provide standard clinical parameters, but also additional information that is not available via traditional assessment.

Janssen *et al.* [115], characterised the STS transition using a pair of uni-axial accelerometers attached to the trunk and thigh. STS transfers were assessed at different speeds and in different styles. Subjects were asked to perform STS transfers with exaggerated flexion of the trunk for example. Janssen *et al.* found the acceleration signals were highly repeatable and sensitive to the way in which the STS transfers were performed. Apart from demonstrating the ability of wearable devices to assess STS transfers, this work demonstrates the potential to extract features that relate to the way a

STS transfer is performed. It would be interesting to see if such features could be used to discriminate between various target groups such as fallers.

Janssen *et al.* [116], further evaluated the reliability of accelerometer measurements of STS using the same combination of sensors attached to the trunk and thigh. The STS duration estimated from the acceleration signals were compared to a gold-standard reference obtained via video recordings of the STS transfers. They found a very high correlation between the accelerometer based duration and the duration extracted from the video recordings, ($\rho = 0.99$, $P < 0.01$). The authors concluded that accelerometry provides a reliable means of assessing the STS transfer.

Giansanti and Maccioni [117] developed an ambulatory monitor, worn on the back at the level of L5 (5^{th} lumbar vertebrae), combining a tri-axial accelerometer and tri-axial gyroscope, to evaluate STS transfers in the elderly. An algorithm was devised, using acceleration and angular velocity during an STS transfer, to identify the endpoints of an STS transfer and estimate the STS transfer duration. The algorithm was validated against video-based measurement of STS transfer durations, in 60 subjects aged between 17-82 years of age. They found the ambulatory monitor was able to measure the duration of the transition to within 25 milliseconds.

In a more complex evaluation of the STS transfer, Giansanti *et al.* [118] used a wearable monitor attached on the back at the level of L5, made up of a tri-axial accelerometer and tri-axial gyroscope, to reconstruct the position and orientation of the trunk during an STS transfer. The reconstructed position and orientation was found to be within 5.9 mm and 0.52 degrees of the position and orientation obtained via video recordings, respectively, in a study of 30 subjects aged between 17-81 years of age. The utility of the system in terms of identifying age-related differences in STS transfers and the monitoring of recovery from injury were discussed. This study highlights the added value simple wearable devices provide over traditional evaluation methods. Traditional assessment of STS involves measuring the time to complete the transfer using a stop watch. Ambulatory monitors provide a far more detailed assessment of the functional task.

Bidargaddi *et al.* [119] used a waist-mounted tri-axial accelerometer to estimate the duration of STS and stand-to-sit transitions using the signal vector magnitude (SVM), the magnitude of each of the acceleration samples. An algorithm devised to estimate the postural transition durations was evaluated in a cohort of young and geriatric subjects on varying types of seats including, a couch, high chair, low chair, and a standard height chair. While performance of the algorithm is not reported, the use of the SVM is quite interesting. The authors noted that since the SVM combines information from all three accelerometer axes, it is independent of the orientation of the device, thus making it a suitable signal to process in situations where device placement cannot be guaranteed. This is certainly true in unsupervised ambulatory applications.

More recently, Zijlstra *et al.* [120], described a novel method for the evaluation of power during STS transfers using wearable sensors combining accelerometers, gyroscopes and magnetometers. Sensors were placed on the hips and sternum. The data from these sensors were used to estimate the vertical acceleration of the body. The acceleration times the body mass of the subject was used as a measure of power. The method was validated by taking simultaneous measures of the STS transfer using a force plate and the body worn sensors. It was found that the estimates of power obtained from the sensors attached to hip, provided the greatest agreement with the measures of power from the force plates. The authors discussed the utility of the system as a measure of lower-limb strength in the elderly. Muscle strength is an established risk factor of falls in the elderly. A simple tool to estimate muscle strength is thus useful in falls risk assessment in the elderly. This study again demonstrates the power of simple sensors to indirectly assess useful clinical parameters.

The TUGT is a composite mobility task involving postural transitions and gait. The TUGT has been suggested as a useful screening tool for falls in the elderly and has been used to subjectively evaluate functional ability in the elderly. Typical clinical assessment involves using a stopwatch to time how long the test subjects takes to complete the movement. Recently, wearable devices have been constructed to quantitatively evaluate the TUGT.

Higashi *et al.* [121] used a pair of wearable sensors, made up of tri-axial accelerometers and tri-axial gyroscopes, attached to the back at the level of L2 and on the thigh, to quantitatively evaluate the TUGT in a study of 20 elderly subjects (half that were able to ambulate independently and the other half that required assistance). A custom algorithm, processing acceleration and angular velocity data from the back and thigh, was used to segment the TUGT into each of its phases, namely standing, walking to the 3 m mark, turning around, walking back to the chair, turning to sit and sitting. The segmentation was validated against timings marked by a therapist observing the TUGT tests. The automatic segmentation was found to correlate well with the timings recorded by the observer. Parameters were extracted from each phase of the TUGT, including cadence, gait variability measures, as well as the RMS acceleration for each of the TUGT phases. The study showed that a number of the extracted parameters differed significantly between elderly that were able to perform the TUGT independently, and those that required assistance. This again shows the added value of wearable ambulatory monitors, in assessing function, and generating parameters sensitive to functional ability in elderly subjects.

Zampieri *et al.* [122], developed a complex system of wearable sensors, attached to the ankles, wrist and sternum, to comprehensively evaluate the TUGT in subjects with Parkinson's disease. The sensors measured accelerations and angular velocities, at the various sensor locations, using accelerometers and gyroscopes. The sensor data was used to evaluate a number of parameters, including arm swing velocity, arm swing range of motion, temporal gait parameters, trunk rotation and range of motion, turning velocity

and sitting velocity, in addition to the clinically evaluated TUGT duration. The study found that the TUGT duration did not discriminate between healthy subjects and those with Parkinson's disease, however, a number of the parameters extracted from the wearable sensors did. In addition, a number of the extracted parameters were significantly correlated with scores from a motor scale used to assess Parkinson's disease patients.

Gait analysis, is the study of human walking which is typically assessed using complex instrumentation measuring body movements during walking. A number of well-established parameters of gait have been evaluated and associated with functional mobility and falls risk in the elderly. Wearable devices have been developed to estimate these parameters in a more portable manner.

Aminian *et al.* [123], used a pair of sensors, measuring angular velocity with uni-axial gyroscopes, attached to the thigh and calf to measure spatial and temporal parameters of gait. Temporal parameters, including gait cycle duration, left stance time, right stance time and double support time and spatial parameters, including stride length and stride velocity were extracted using a wavelet-based analysis of the sensor data. The measures were validated against those obtained via foot-switches. A very high correlation was found between parameters extracted from the wearable sensors and those obtained from the foot-switches. The authors suggested that such a system could be used as a diagnostic tool for abnormal gait, as a predictor tool for falls risk or as a long-term monitoring tool to assess progress during rehabilitation.

Moe-Nilssen *et al.* [124], used a tri-axial accelerometer, attached to the back, at the level of L3, to estimate a number of gait features. Cadence, step length and a similarity metric, assessing the repeatability of gait cycles, were computed from the autocorrelation coefficients for each of the sensitive axes of the accelerometer. This study showed that gait features, normally obtained using specialised laboratory equipment, could be obtained from a simple body worn ambulatory monitor that could provide a more portable means of assessing gait.

In a second study, Moe-Nilssen *et al.* [125], measured inter-stride trunk acceleration variability in a group of fit and frail elderly subjects. Using the system described in [124], variability measures were extracted from autocorrelation coefficients for each accelerometer axis. The extracted variability measures were found to discriminate between fit and frail elderly with a sensitivity and specificity of 75% and 85%, respectively. This study illustrates the potential of gait parameters extracted from wearable monitors to discriminate between varying groups of elderly subjects. Naturally, such parameters may be able to distinguish between elderly fallers and non-fallers, for example.

Dijkstra *et al.* [126], evaluated the accuracy of a tri-axial accelerometer based ambulatory monitor, attached to the waist, in detecting periods of walking and the number of steps in study of older adults (n = 20) and those with Parkinson's disease (n = 32). Gait was assessed over varying distances and speeds and with the subjects sometimes performing a

dual task such as counting or carrying a tray. They found the accelerometry-based measurements less accurate at higher walking speeds and at shorter distances. In particular, the error in the number of steps detected was quite high during short distance walking tests. This study enables better design of assessments of gait using accelerometer-based ambulatory monitors, as it provides a guide for the speed and distance that is needed for accurate results. Additionally, they found subjects quite accepting of a single waist-mounted wearable device for ambulatory monitoring.

Lindemann *et al.* [127] evaluated gait in 116 community-dwelling elderly, with a mean age of 83.1 years. Gait was evaluated by measuring lower-limb movement using a pair of sensors, measuring angular velocity, attached to the thigh and calf. The study looked to evaluate the distance required to achieve steady state walking and the effect distance has on measures of gait variability. A custom algorithm was devised to identify the time at which steady state walking is reached. The study found that 90% of elderly subjects achieved steady state with 2.47 m of walking. The study also showed the measures of gait variability were dependent on distance. They concluded that analysis of gait should omit the first 2.5 m of walking data and that variability measures should be made over fixed distances to ensure comparisons can be made. Like the work done by Dijkstra *et al.* [126], this study provides information on how gait should be assessed using body worn ambulatory monitors.

Zijlstra [128] developed a tri-axial accelerometer based ambulatory monitor, attached to the trunk, to measure a number of temporal and spatial parameters of gait in a study of 26 healthy subjects and 15 healthy elderly subjects. Left and right foot contacts were reliably detected, enabling individual steps, stride times and the variability of the measures to be evaluated. Vertical accelerations were used to evaluate step length, using the subject's leg length to calculate it. Step length combined with step duration was used to evaluate walking speed. Zijlstra reported a miniaturised version of the device could be used for long term monitoring of gait parameters.

From the summaries of the body-worn ambulatory monitors evaluated, it can be seen that such systems provide a convenient means of evaluating various parameters relating to measures of functional ability and mobility in the elderly. Gait parameters, muscle strength, postural stability and activities of daily living could be evaluated using simple body-worn systems. A number of these parameters are readily assessed in falls risk assessments and thus, the potential for ambulatory monitors to aid in the evaluation of falls risk is evident.

2.5.2.3 Falls risk assessment

Considerable effort has gone into developing ambulatory monitoring systems for the real-time detection of falls and functional assessment of elderly. What is apparent from the literature, is that there is an immense potential for ambulatory monitoring systems to be

extended to the evaluation of falls risk in the elderly. A number of functional assessment tasks such as, STS transfers, gait and standing balance are readily evaluated by way of simple ambulatory monitors and have been demonstrated to be useful in the evaluation of falls risk. Despite this, limited work has been done on the evaluation of falls risk using ambulatory monitors.

In 1998, Cho and Kamen [129] assessed 16 elderly subjects, 8 healthy subjects and 8 fallers, using accelerometers placed at the head and hip. Standing balance was evaluated while the subjects stood on firm or compliant surfaces with eyes either open or closed. Additionally, common clinical measures of balance were assessed namely, the Romberg test, functional reach test, rapid stepping test and heel-to-toe transition test. Parameters extracted from the acceleration data during standing balance tests were compared to the clinical measures of balance in the cohort of subjects. Interestingly, the accelerometer parameters performed better than the two of the commonly used clinical measures of balance, the functional reach test and heel-to-toe transition test, with the accelerometer parameters and performance in the Romberg test and rapid stepping test being significantly different between healthy elderly and fallers. The authors remarked that accelerometry is an inexpensive and clinically useful technique for distinguishing between healthy elderly and fallers.

Najafi *et al.* [130], evaluated falls risk using an ambulatory monitor, comprised of a single axis gyroscope, attached to the sternum, in a sample of 11 elderly subjects over the

age of 65. Subjects were assessed for falls risk using a combination of known risk factors including falls history, medications use, balance impairment, gait disorders, vision impairment and cognitive function. The parameters assessed and the scoring system is shown in Table 2.2. Subjects were classified as fallers if they obtained a score of 5 or more, otherwise they were classified as non-fallers. Functional ability was assessed with the ambulatory monitor via the performance of Sit-To-Stand (SiTS) and Stand-To-Sit (STSi) transitions. Tests involved performing three of each of the postural transitions. The ambulatory monitor measures the rotation of trunk and is processed to evaluate the time taken to perform and the number of false attempts required to perform the transition. The average postural transition time, the standard deviation of the postural transition times and the total number of false attempts to perform were evaluated as falls risk variables. It was found those in the high risk group (falls risk score of 5 or more), had higher postural transition times, increased variability in postural transition times and were more likely to require multiple attempts to perform postural transitions.

Table 2.2 – Falls Risk Index. Adapted from [130].

Parameters	**Score**
History of falls in the preceding year	No = 0 / Yes = 2
Static equilibrium disturbances	No = 0 / Discrete = 1 / Marked = 2
Gait disturbances	No = 0 / Discrete = 1 / Marked = 2
Troubles of vision	No = 0 / Discrete = 1 / Marked = 2
Troubles of cognition	No = 0 / Discrete = 1 / Marked = 2
Troubles of mood	No = 0 / Discrete = 1 / Marked = 2
Falls-risk score	**Total score _____**

Najafi *et al.* [131], modified the falls risk assessment in another study involving 11 community-dwelling elderly, aged 79 ± 6 years. Again, a custom falls risk score was assigned using a combination of known risk factors, including balance and gait disorders, falls history, visual impairment and cognitive and depressive disorders. The modified risk assessment and rating system is shown in Table 2.3. Balance and gait disorders were evaluated using the Tinetti score and supplemented a self-reported history of falls and physician's assessment evaluating visual impairment and cognitive and depressive disorders in the elderly subjects. Like in the earlier study [130], a score of 5 or more in the assessment was interpreted as being indicative of a high risk for falls. Parameters were extracted from tests of functional ability involving SiTS and STSi postural transitions. Similar to the first study, it was found those in the high risk group, had higher postural transition times, increased variability in postural transition times and were more likely to require multiple attempts to perform postural transitions. Optimum cut-points for the parameters were not evaluated for the discrimination of those at high risk of falls.

Table 2.3 – Falls Risk Index. Adapted from [131].

Parameters	**Score**
Balance disorders	No = 0 / Discrete = 1 / Marked = 2
Gait disorders	No = 0 / Discrete = 1 / Marked = 2
History of falls in the preceding year	No = 0 / Yes = 2
Vision impairment	No = 0 / Discrete = 1 / Marked = 2
Cognitive disorders	No = 0 / Discrete = 1 / Marked = 2
Depressive Symptoms	No = 0 / Discrete = 1 / Marked = 2
Falls-risk score	**Total score _____(0 to 12)**

In contrast to the single sensor system evaluated by Najafi *et al.* [130-131], Menz *et al.* [132-133], investigated a dual-sensor system in which parameters extracted from accelerations of the head and pelvis during gait, were evaluated against falls risk in elderly subjects. In a preliminary study of 30 young healthy subjects [132], parameters extracted from accelerations measured at the head and pelvis during walking assessments on level and irregular surfaces were analysed. The parameters included walking velocity, cadence, average step length, step timing variability and the harmonic ratio of odd and even harmonics, using stride frequency as the estimate of the fundamental frequency, extracted from the head and pelvis accelerations. It was found that the harmonic ratio was lower when walking on irregular surfaces compared to level ground. That is, gait was less periodic on irregular surfaces. The harmonic ratio was subsequently assessed in a study of 100 community-dwelling elderly aged 79.7 ± 4.0 years, assessed for risk of falling using the Physiological Profile Assessment (PPA) described in Section 2.3.2. It was found that elderly with increased falls risk, as determined by the PPA, had significantly lower harmonic ratios when walking on both level and irregular surfaces as measured by accelerations at both the head and pelvis. Again, an optimal cut-point for harmonic ratio at either the head or pelvis was not determined. While not discussed, this method certainly has potential as a screening tool for falls risk in the elderly. A simple measurement of walking on a level surface is all that is required.

A considerable amount of work using ambulatory monitors for the evaluation of falls risk in the elderly has been reported by Giansanti *et al.* [134-137]. Giansanti developed an ambulatory monitor, combing accelerometers and gyroscopes, worn at the back at the

level of L5 on the lumbar spine. The ambulatory monitor characterises movement in terms of accelerations and rotations. The ambulatory monitor was used to evaluate postural stability, by way of body sway measurements, on firm and compliant surfaces with eyes open and closed. The mean magnitude of the angular velocities measured, during each postural stability test, was extracted. The ratios of the mean magnitudes during balance tests with eyes open and closed on a compliant surface with the mean magnitude during balance test with eyes open on a firm surface were taken as the performance metrics.

In a study involving 390 subjects [135], falls risk was evaluated using a version of the Tinetti balance test. 90 subjects were used to form a training set in which, 30 subjects with age < 65 and a Tinetti score = 1 formed the control group. 30 elderly subjects, age > 65, with a Tinetti score of 1 formed the low falls risk group and 30 elderly subjects, age > 65, with a Tinetti score of 3, formed the high falls risk group. The ambulatory monitor balance performance metrics obtained during assessment of postural stability, were evaluated using cluster analysis to form clusters for each of the training groups. 300 validation subjects, 100 subjects for each of the training groups, were used to validate the performance of the classifier. A sensitivity of 93.9% and specificity of 93.0% was achieved in discriminating between elderly at high risk for falls and elderly at low risk for falls. The performance of the system was enhanced using a neural network trained to classify elderly into the low-risk or high-risk groups [136]. The neural network-based classifier, had a sensitivity and specificity of 98% and 97%, respectively in classifying elderly subjects as either low-risk or high-risk for falling.

In a separate study, also involving 390 subjects [134], a neural network classifier was developed to identify subjects at each of the three levels of the Tinetti Scale used to assess falls risk in the study. 90 subjects, were used to train the neural network, 30 subjects in each level of the Tinetti scale aged between 43 and 84 years of age. A multi-layer neural network was derived, using 272 neurons, to classify subjects into the three falls risk groups. The classifier was validated using the data from 300 validation subjects, 100 at each level of the Tinetti scale and aged between 42 to 83 years of age. The neural network performed quite well with a sensitivity and specificity of 91% and 92%, respectively, discriminating between those at level 1 of the Tinetti scale and those at level 3. A sensitivity and specificity of 87% and 88%, respectively, in discriminating between those at level 2 and level 3 was achieved and a sensitivity and specificity of 88% and 89%, respectively, in discriminating between those at level 1 and level 2 of the Tinetti scale was achieved.

Giansanti *et al.* [137], extended the falls risk assessment by developing a system for the remote evaluation of falls risk in the elderly. The assessment of risk evaluated in a number of studies [134-136] was incorporated into a remote assessment in which the falls risk classification was sent, via the Global System for Mobile communication (GSM) network using a Short Message Service (SMS) message that coded the falls risk score. The falls risk assessment was carried out, remotely, 20 times and the SMS was received 100% of the time. Interestingly, the system is presented as a system suitable for the remote assessment of falls risk despite requiring the subjects to stand on a compliant surface with eyes closed and unassisted, to evaluate falls risk.

Marschellok *et al.* [138], looked to develop combinations of falls-risk assessments for the elderly, using a single, waist-mounted tri-axial accelerometer. In a study of 110 geriatric in-patients, parameters extracted from the ambulatory monitor were compared against commonly used clinical tools for falls risk in the elderly namely, the TUGT (see Section 2.3.1), STRATIFY [139], which is used to identify geriatric in-patients at risk of falling, and the Barthel Index [140], used for functional evaluation. When the subjects performed the TUGT, they wore the ambulatory monitor which measured accelerations at the waist. A periodogram was calculated for the vertical acceleration data from which a number of frequency based features were extracted. The suggested cutoff points for each of the clinical assessment tools were used to group subjects into high falls risk and low falls risk groups. Logistic regression models were derived for each of the clinical assessment tools using the frequency based features. The performance of the models was evaluated by comparing them to the classifications of clinical assessment tools. The sensitivity and specificity for the TUGT, STRATIFY and Barthel Index models were, 99% and 15.4%, 78.5 % and 46.7% and 79% and 60.4%, respectively.

In a second study, Marschellok *et al.* [141], combined the data from three commonly used clinical assessments of falls risk, with sensor data obtained from a waist-worn ambulatory monitor, to create a model of falls risk to identify geriatric in-patients at risk of falling. The ambulatory monitor was used to assess functional ability using the TUGT from which, extracted parameters relating to energy expenditure, pelvic sway, step length, number of steps and frequency were evaluated. The ambulatory monitor based parameters were combined with parameters obtained via the TUGT, STRATIFY and

Barthel Index, clinical falls risk assessment tools, which included parameters relating to falls history, visual impairment, mobility and medications use. A CART model was developed using falls logs maintained by the hospital. The combined model was assessed in 110 geriatric in-patients and found to have a sensitivity of 57.5% and specificity of 100% in classifying fallers from non-fallers. A combined model, using parameters from the clinical assessment tools only, was found to have a sensitivity of 38.5% and specificity of 97.6% in classifying fallers from non-fallers. In this study, the sensory information obtained from the ambulatory monitor, significantly improved the performance of clinical assessment tools in discriminating between elderly fallers and non-fallers. The simple assessment of the TUGT, using a single waist-mounted accelerometer, is quite feasible for in-patient assessment and has been shown to aid in the identification of fallers.

A similar approach was taken by Gietzelt *et al.* [142], in a study of 241 elderly subjects, functionally assessed using a single waist-mounted tri-axial accelerometer via the TUGT. Various gait parameters were extracted from the acceleration data. Falls risk was ascertained using the STRATIFY clinical falls risk assessment tool for geriatric in-patients. Low risk and high risk groups were formed on the basis of the subject's STRATIFY score. A decision tree was derived to classify a subject's falls risk using the gait parameters extracted from the acceleration data. The model had a sensitivity and specificity of 89.4% and 91.0% in classifying subjects as either low risk or high risk of falling. The authors reported that, given the simple nature of the assessment, the system

could be used for the longitudinal assessment of falls risk, however, the system needed to be evaluated for acceptance.

de Bruin *et al.* [143], evaluated an ambulatory monitoring system for the free living monitoring of elderly and used to assess falls efficacy. The ambulatory monitor was attached to the chest and comprises of a single axis gyroscope, measuring rotation in the mediolateral plane, and a biaxial accelerometer measuring accelerations in the vertical and anteroposterior planes. In a study of 11 elderly subjects, aged 87.8 ± 2.5 years of age, falls efficacy was assessed using the Falls Efficacy Scale (FES), described in Section 1.2.3.1, which evaluates the subject's confidence in performing daily tasks without falling. The FES has been used to discriminate between fallers and non-fallers in the elderly. Free living recording were taken over two consecutive days, for 11 hours per day, in which posture, postural transitions and walking were detected from the recordings. The authors found a significant correlation between the scores in the FES and the mean SiTS times, ($\rho = 0.84$, $P < 0.01$). The more confident the elderly were at performing daily tasks, the lower the SiTS times. The authors found the system unobtrusive and showed the potential of continuous monitoring. They also found the system feasible, with participants quite tolerant of the ambulatory monitoring system.

Rochat *et al.* [144], evaluated the effect of a 10-week gait and balance training program on gait and falls efficacy, using an ambulatory monitoring system using gyroscopes attached to the thigh [123]. In a study of 47 community-dwelling elderly, with reported

gait and balance problems, gait was evaluated using the ambulatory monitor with the subjects walking 20 m at their own pace. A number of gait parameters were extracted from the recording including, gait speed, stride length and double support time. Falls efficacy was evaluated using the FES previously described. Baseline measurements were taken prior to a 10-week low-intensity balance and gait training program and one week after the conclusion of the program. Slight improvement were found in gait speed, with improvements more pronounced in those lower falls efficacy (FES score < 100). Interestingly, this study highlights the utility and potential of ambulatory monitoring devices in evaluating the effects of interventions in the elderly. Being able to monitor the effect of interventions would enable improved management of interventions. They could be altered if found not to have an effect.

Looking at the work being done using ambulatory monitors to assess falls risk in the elderly it is clear that the general approach is to model clinical assessment tools using features extracted from ambulatory monitors. The systems trialed vary in sensor type and device placement. Few studies have looked to validate the developed ambulatory monitor assessments of falls risk against reliable falls data [141]. For the most part studies have looked to evaluate falls risk to identify elderly at increased risk of falling. Studies have not looked at identifying particular physiological deficits in addition to discriminating between those at low risk for falls and those at high risk of falls. What is certain is the immense potential for ambulatory monitors to assess falls risk and functional ability in the elderly.

2.6 Chapter conclusion

This chapter provides an understanding of the implications and consequence of falls in the elderly. Risk factors for falls were described. The falls risk screening tools, as well as, the comprehensive falls assessments, using these risk factors were described. These tools vary in approach, from simple questionnaires to comprehensive physiological evaluation, and outcome, some tool attempt to identify fallers, while other are interested in identifying recurrent fallers or those likely to suffer injuries. Interventions to prevent falls were described. Single interventions, applying one major category of intervention, multiple interventions, applying two or more categories of intervention, and multifactorial interventions, providing individualised interventions have been trialed. A number of interventions have been successful in reducing the rates of falls and falls risk in the elderly. Wearable ambulatory devices, used to monitor and evaluate the elderly were described. Long-term monitors for the real-time detection of falls have shown to be capable of detecting numerous types of falls. A number of studies have shown the ability of body-worn sensors to evaluate gait, balance and functional ability in the elderly, all of which are related to falls risk. Additionally, a number of studies looked to evaluate falls risk or identify elderly at risk, using wearable devices. The following chapter describes the tri-axial accelerometer-based wearable monitor used in this work, to provide an unsupervised assessment of falls risk in the elderly. A clinical monitoring system for the supervised assessment of the elderly is described, and a home monitoring system for the unsupervised assessment of the elderly is described. The characteristics of the signals obtained via the ambulatory monitor are presented.

3 The ambulatory monitoring system

3.1 Introduction

A tri-axial accelerometer based-ambulatory monitoring system was designed to evaluate functional ability in the elderly. The system was designed to be used in a clinical setting as well as, in an unsupervised home environment. The wearable component of the system is based on the ambulatory monitor described by Mathie [145] and Karantonis *et al.* [86].

The system is based on a wearable ambulatory monitor (TA)[1] comprising of a single, tri-axial accelerometer and Bluetooth transceiver. In a clinical setting, the TA interfaces to a laptop computer via a Bluetooth link and allows movement data to be streamed to the laptop in real-time. In an unsupervised environment, the TA interfaces to a receiver unit (Portal) via a Bluetooth link and is designed to guide users through a set of movements known as the directed routine (DR). The DR is described in Chapter 4. The Portal is designed to connect to the internet via broadband, through a Local Area Network (LAN), or establish a dialup connection using a modem. Collected data can then be automatically uploaded to a server for processing.

The first sections of this chapter describe the design of the system and modes of operation. Later sections discuss characteristics of the TA signal and device placement.

[1] TA is an abbreviation for Tri-axial accelerometer but in this context refers to the entire wearable ambulatory monitor.

It should be noted the current author was involved in the specification of the system and played the primary role in the design and implementation of the firmware for the TA and clinical monitoring software. The TA and Portal were built by engineers at the Biomedical Systems Laboratory at the University of New South Wales, Sydney, Australia.

3.2 System requirements

3.2.1 TA requirements

The wearable ambulatory monitor, the TA, is required to be used in a clinical study, in a falls clinic environment and by the elderly, in an unsupervised home-based environment. Each setting, when considered in isolation, has highly contrasting constraints. In a clinical environment, with a clinician or researcher providing assistance to test subjects, a device can be considerably more complex in terms of user interface and device placement than a device that is required to be used by an elderly subject, unsupervised, where all the complexity of the monitoring system should be as abstracted as much as possible from the user, in order to make the system as simple to use as possible. As such, the constraints placed on the TA in terms of, use in an unsupervised setting, dictates the requirements for the TA.

Mathie [145], described the requirements for a waist-mounted TA-based monitoring system, used in an unsupervised setting, in terms of maximising compliance, placement of the device and performance of the sensors. Irrespective of the utility of the system, if compliance with the system is poor, any benefit gained by using the system is lost. Understandably, a system simple and comfortable to use were the key requirements set by Mathie. Comfort is achieved by ensuring the device is as light and small as possible without making it difficult attach to the body or too small to effectively use. If the user forgets that they are wearing the device then, the dimensions, weight and attachment mechanisms are suitable.

The most fundamental requirement however, is that the accelerometer used in the TA has adequate sensitivity and bandwidth to measure body movement at the level of the waist. Additionally, the battery life of the device should be sufficient to allow the TA to be used for the required amount of time.

To summarise, the requirements for the TA are:

1. Simple to use unsupervised;
2. Comfortable to use;
3. Have adequate sensitivity and bandwidth;
4. Have adequate battery life.

3.2.2 Clinical monitoring requirements

The TA is required to interface to a laptop computer, via its Bluetooth link, in order to stream movement data in real-time. In addition to being able to stream data, the clinical monitoring system was designed to allow annotation of the real-time data stream. That is, place fiducial markers into the raw acceleration stream to mark particular events within a movement.

3.2.3 Home monitoring requirements

The TA, in combination with a receiver unit, the Portal, is required to implement a directed routine of movements (see Chapter 3). That is, guide a user through a set of movement tasks in a simple manner, store collected data on the Portal and upload the data to a remote server for processing.

3.3 System design

3.3.1 The TA

Figure 3.1, shows the dimensions of the TA. The TA is enclosed in a small case, 71 x 50 x 18 mm, weighs approximately 55 g and has a large red push-button on its front face. Mathie *et al.* [104], in a pilot study of the TA reported that a number of subjects found the placement of a switch on the top surface of the TA caused some discomfort, as the

switch often pressed into the body when sitting. Placing the switch on the front surface of the

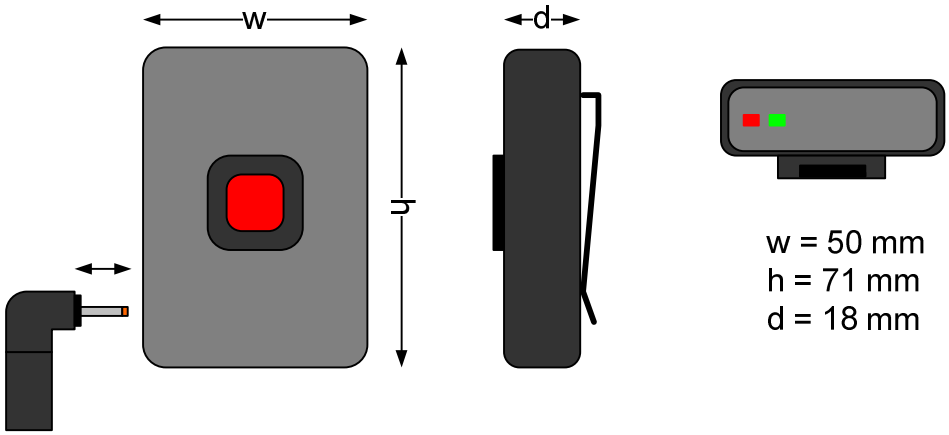


Figure 3.1 - Mechanical drawing of the TA showing the dimensions of the TA and the location of the push-botton switch and feedback light-emitting diodes.

enclosure increases accessibility to the switch and alleviates discomfort caused by the switch pressing against the body. The push-button provides the only means of user input to the TA. Two light-emitting diodes (LEDs), see the top view in Figure 3.1, are placed on the top surface of the enclosure and provide information about the state of the TA to the user. A piezoelectric buzzer is enclosed in the case and also can provides feedback to the user. A clip on the rear side of the enclosure, as shown in the side view in Figure 3.1, allows the TA to be fastened to a belt or pants as shown in Figure 3.2. The accelerometer sensor is aligned such that its sensitive axes, x, y, z, relative to the body, measure medioloateral accelerations, anteroposterior accelerations and vertical accelerations, respectively. The effects of device placement are discussed in Section 3.4.

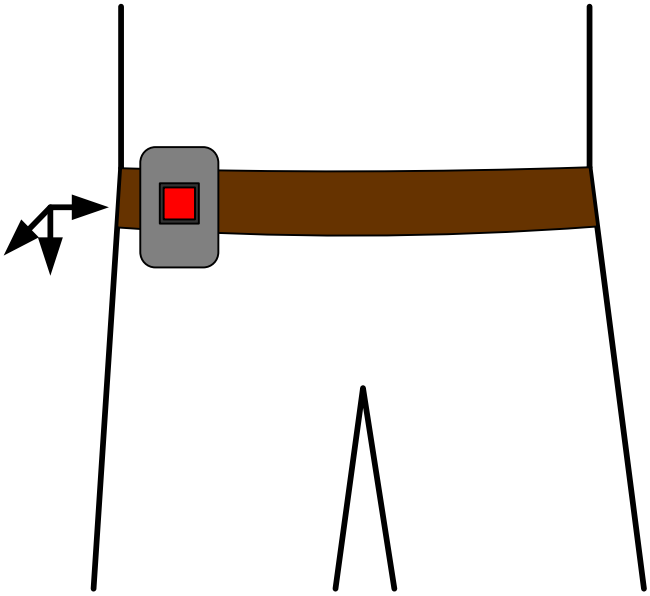


Figure 3.2 - Placement of the TA at the level of the waist.

Figure 3.3, shows a block diagram of the TA, hardware design. At the heart of the TA is the MSP430f149 mixed signal 16-bit RISC microcontroller manufactured by Texas Instruments Inc operating at 8.0 MHz. The MSP430f149 incorporates an eight-channel 12-bit analog-to-digital converted (ADC). A tri-axial accelerometer, the MMA7260Q from Freescale Semiconductor interfaces to three channels of the microcontrollers ADC port. The analog accelerometer data is sampled at 640 Hz and down-sampled to 40 Hz using an FIR filter to band-limit the signal to approximately 17.75 Hz, less than the Nyquist rate. The triaxial accelerometer data is buffered at 40 Hz. A Class-1 Bluetooth module, interfaces serially, via universal asynchronous receiver/transmitter (UART) ports between the Bluetooth module and microcontroller. The main programming loop of the microcontroller continuously polls the internal buffer, containing sampled accelerometer data, as quickly as possible looking for new data to pump through the Bluetooth link. Polling of the internal buffer provides least latency between sampling and transmission of

accelerometer data. A large 15 mm diameter push-button switch, interfaces to a digital I/O port on the microcontroller capable generating interrupts when the switch is pressed. An 860 mAh lithium polymer battery powers the TA and can be recharged by an external 6V (DC) AC adapter. Despite the large battery, the device only weighed 57 grams.

Accelerations, relating to human movement, recorded at the waist, range between ±6 g, and have a frequency content between 0-20 Hz, though most of the content lies within 0-3 Hz [145]. The accelerometer used in the TA has a configurable sensitivity between 1.5-6 g and a bandwidth of 150 Hz. Sufficient for the evaluation of human movement. Additionally, the RMS noise of the accelerometer is very small, only 0.142 %FSO (full scale output), which corresponds to 8.52×10^{-3} g at a sensitivity of ± 6 g.

With respect to the requirements for the TA described in section 3.2.1, the small size, light weight and improved placement of the switch make the TA comfortable to wear. A single push-button switch, a single LED and piezoelectric buzzer are used to define the user interface for the purposes of unsupervised home monitoring. It is expected that the simple nature of the interface will make the TA easy to use unsupervised. Naturally, this must be verified. The TA has adequate sensitivity and bandwidth to measure accelerations at the waist for human movement. The relatively large (860 mAh) battery provides more the sufficient battery life.

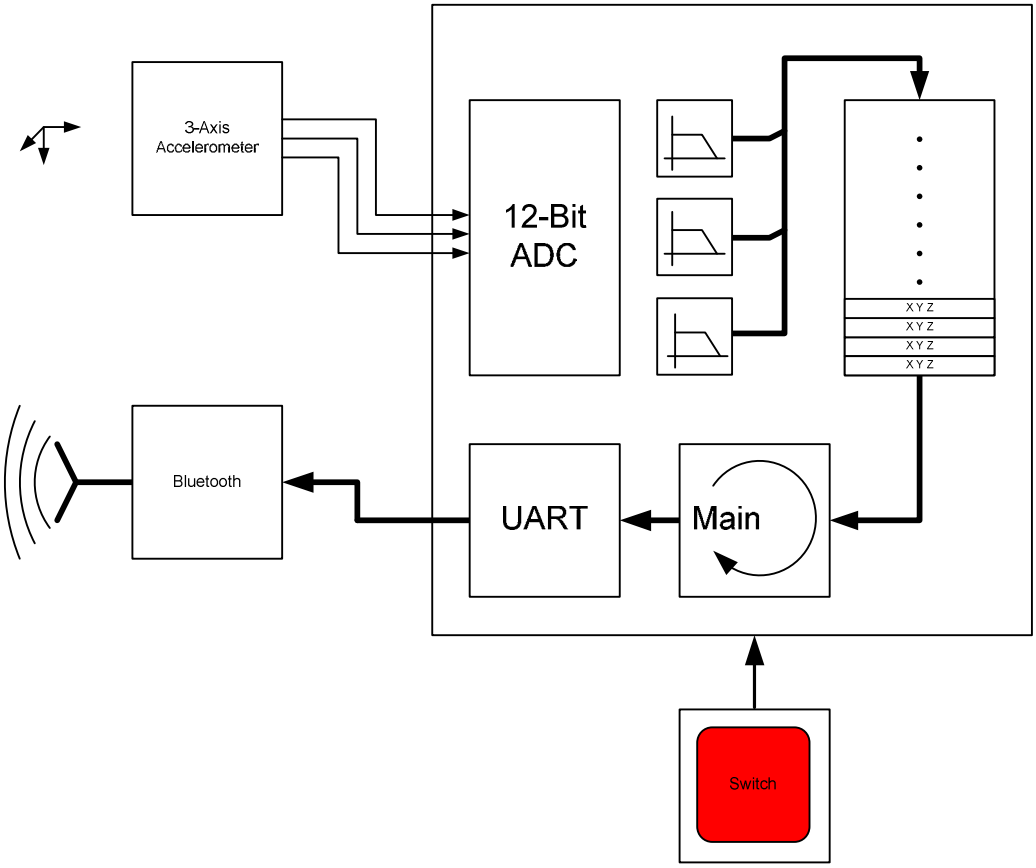


Figure 3.3 - TA hardware architecture.

3.3.2 The clinical monitoring system

Figure 3.4, shows a block diagram of the clinical monitoring system. The TA is configured to establish a Bluetooth connection between the TA and a nearby laptop computer when the push-button switch on the TA is pressed for at least 200 ms. With a wireless connection established, acceleration data is streamed to the laptop as described in section 3.3.1. A custom software application was written to log data arriving at the PC and annotate the data stream.

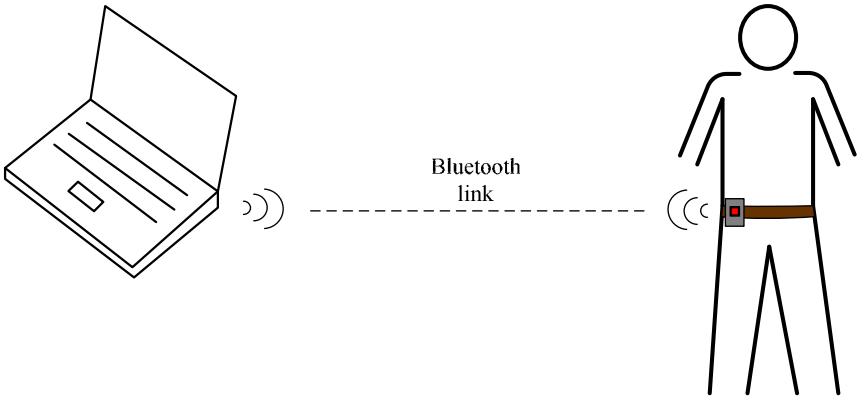


Figure 3.4 - Clinical monitoring system block diagram

The software application polls a virtual serial port (VCP) established between the Bluetooth adapter on the laptop and the software. New data is immediately displayed and written to a log file in which, each line of the log file contains an acceleration sample. That is, the x, y and z acceleration samples, as well as a binary value representing observer annotations. Annotations are generated by an observer pressing the Annotation button in the software. A button press interrupts the software and sets an internal flag. When the flag is set, a '1' is written to the next line of the log file and the flag reset. Figure 3.5, shows a screen shot of the data collection software application in which the annotation button is highlighted. The screen shot also shows an annotation inserted into the data stream. Figure 3.6, shows a representative sample of acceleration and annotation data collected via the clinical monitoring system during an assessment using the timed up-and-go test. The test involves, standing up from a seated position, walking three meters, turning around, walking back to the chair and sitting down as quickly as possible. Figure 3.6 shows the annotations inserted into the data stream and represent the times at which the subject stands up, reaches the three metre mark, completes the turn, reaches the

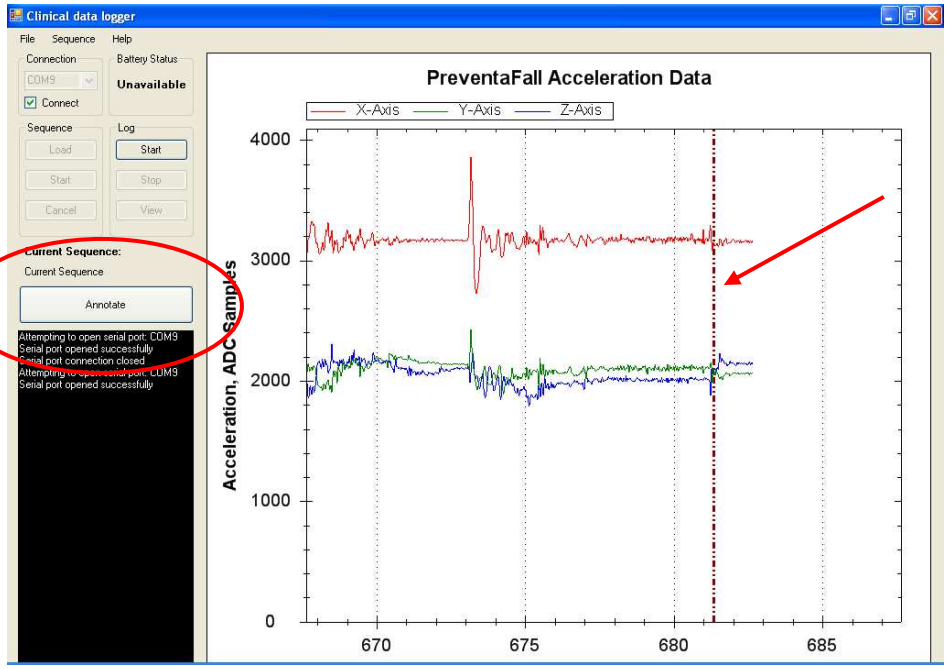


Figure 3.5 - Data collection software. The annotation button is circled and an observer placed annotation is shown.

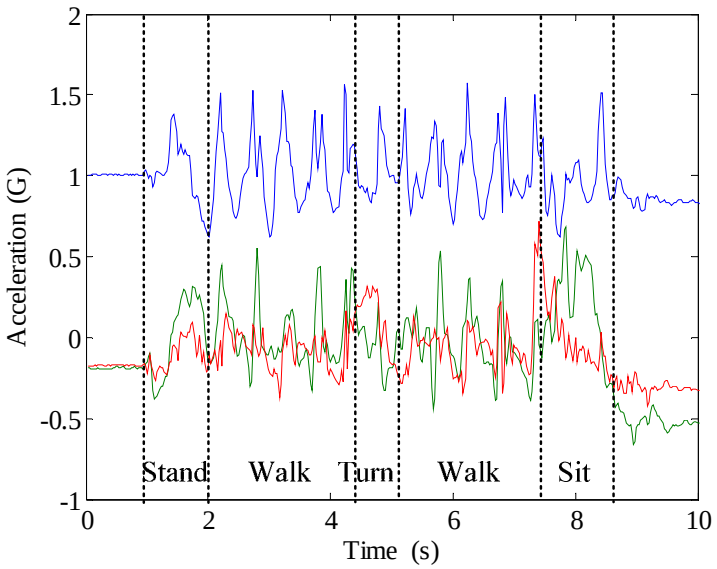


Figure 3.6 - Representative, manually annotated, TA data for the TUGT.

chair and sits down. The manually inserted markers are used to segment the data for processing (see chapter 4).

3.3.3 The home monitoring system

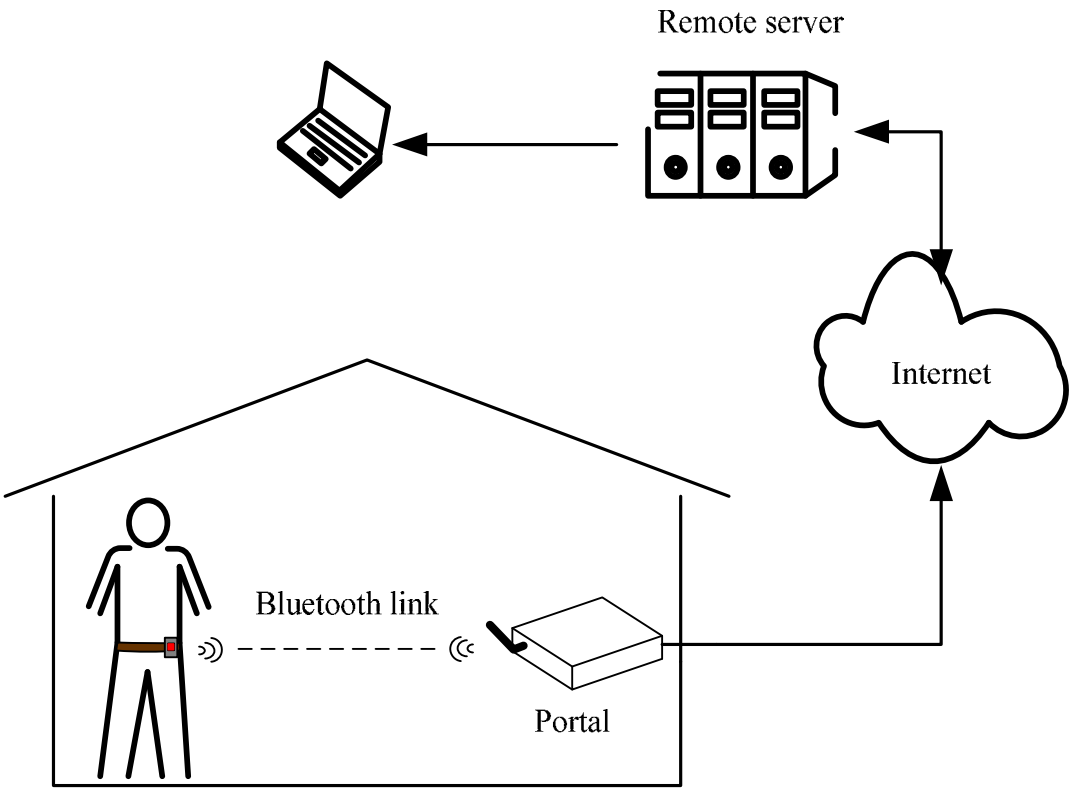


Figure 3.7 - Block diagram of the home monitoring system.

Figure 3.7, shows a block diagram of the home monitoring system that enables unsupervised assessment of mobility in the elderly. The TA interfaces to a receiver unit known as the Portal. The TA in combination with the Portal, implements a directed routine in an unsupervised environment in which, the user is guided through a fixed set of movement tasks. The Portal, via connection to the internet, uploads collected data to a remote server for processing.

In home monitoring mode, the TA is programmed to interface with the Portal in order to administer the directed routine unsupervised. Users are required to wear the device only

when performing the directed routine. With the TA off, plugging the AC adapter into the TA, turns on the device and places the TA in idle mode. When the user removes the AC adapter, the TA establishes a Bluetooth link with the Portal and begins streaming acceleration data which is stored on the Portal. The user then uses the push-button switch on the TA to maneuver through each movement task of the directed routine. Figure 3.8, illustrates the user interface with the TA to perform a directed routine. When a subject is ready to perform the first directed routine task, they press the push-button. After a one second delay, the piezoelectric buzzer with the TA buzzes once a second for three seconds. After the buzzing, the user performs the requisite movement task. When the task is complete, the user presses the push-button switch to signify the end of the task. This process is repeated until all the movements of the directed routine are complete. After the final button press, the TA disconnects the Bluetooth link with the Portal and powers down.

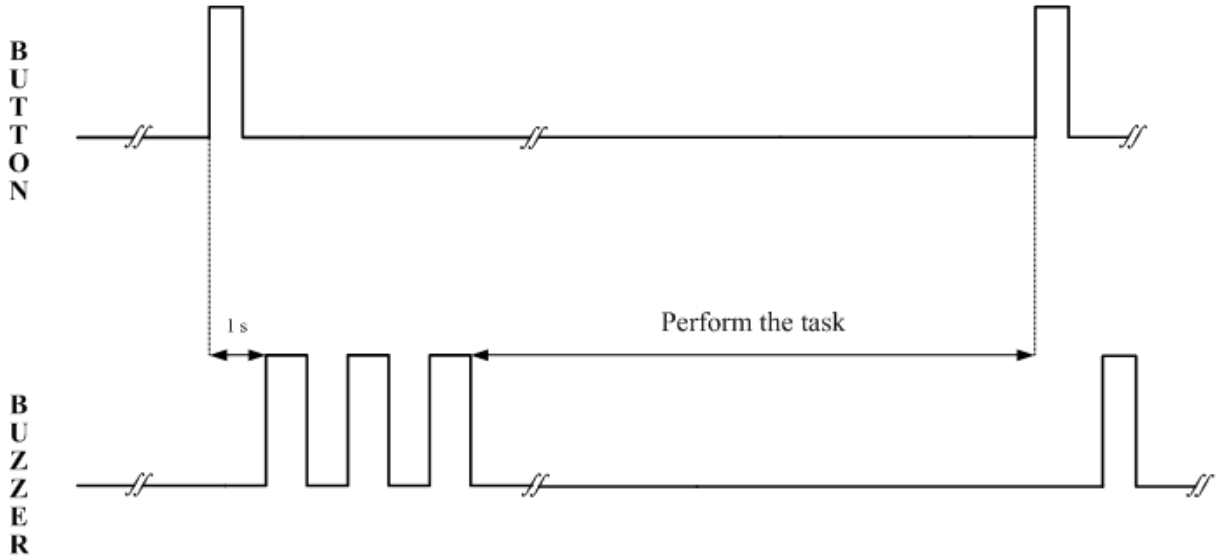


Figure 3.8 - Performing a directed routine task. One second after the user presses the push-button a sequence of three buzzes is played. After the third buzz, the user performs the task. When finished, the user presses the push-button to mark the end of the movement.

3.4 The TA signal

It is important to understand the nature of the signal obtained using the TA. Mathie [145] provides a comprehensive characterisation of the signals obtained using a single, waist-mounted TA. This section aims to provide a concise overview of the signals obtained using the TA. In later chapters, this signal is processed and features extracted. These features are used to model falls risk and functional mobility in the elderly.

The TA uses a MEMS-based tri-axial accelerometer enclosed in a small case worn at the level of the waist. The tri-axial accelerometer contains three, mutually orthogonal, uni-axial accelerometers. The three sensitive axes of the accelerometer form the basis to which, measured accelerations are represented. This means, that the TA measures accelerations, at a particular location on a person's waist, relative to the orientation of the sensitive axis of the TA and not, with respect to a global reference frame. In other words, the TA characterises movement of the body about a point on the waist. This is illustrated in Figure 3.9, which shows the orientation of the TA sensitive axes, $\{X_{TA}, Y_{TA}, Z_{TA}\}$, relative to a reference coordinate system, $\{X_{body}, Y_{body}, Z_{body}\}$, for the body, taken at the midpoint of the waist. If the placement of the TA, relative to the reference coordinate system for the body, is the same each time the device is attached, then accelerations measured by the TA for a given movement will be the same if performed exactly the same way each time. Thus, differences in the accelerations measured are reflective of changes in the way the movement is performed. If this was not the case, then differences

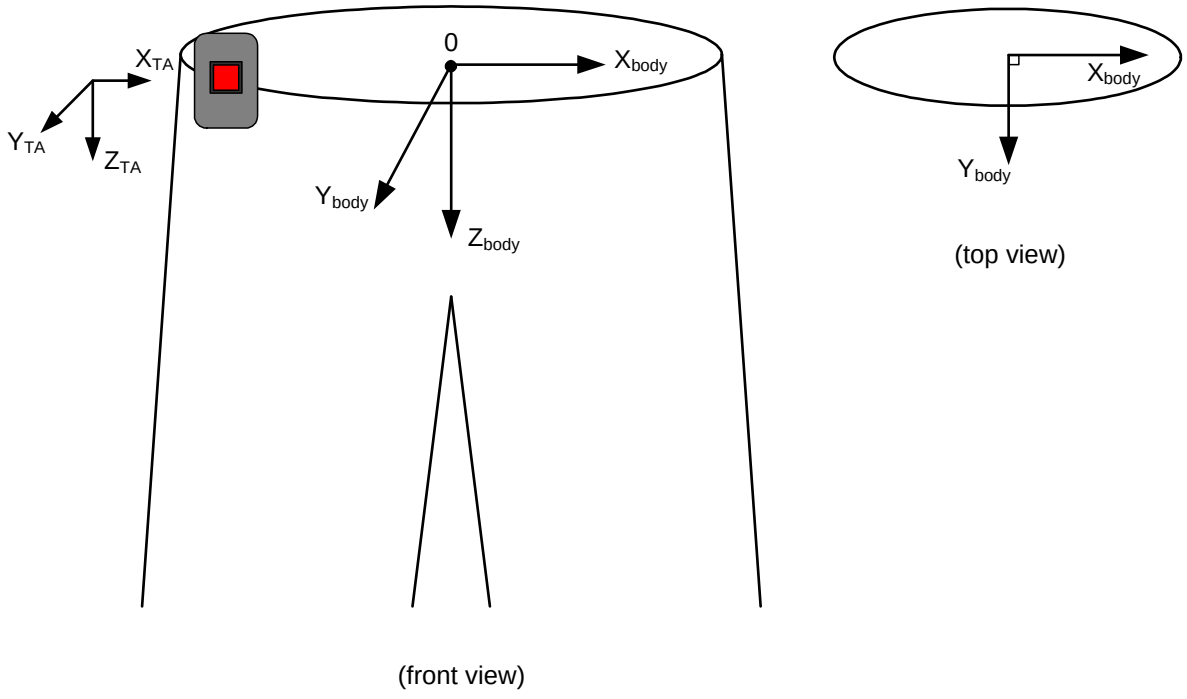


Figure 3.9 - The orientation of the sensitive axis of the TA relative to a reference coordinate system for the body at the level of the waist.

in the accelerations measured by the TA for any given movement would not have any meaning.

The TA is sensitive to more than the accelerations resulting from the movement of the body. The TA is sensitive to both intrinsic accelerations, those caused by movement of the body and system noise, and extrinsic accelerations caused by the environment. Mathie [145] described the TA signal to be a sum of:

1. a gravitational component (GA) due to gravity;
2. a body component (BA) due to the movement of the body;

3. external vibrations not caused by the body (earth quake or moving car for example);
4. artifact caused by the TA unintentionally moving (the TA slipping or knocking into an external object); and
5. noise intrinsic to the accelerometers themselves.

The first two components contain information about the movement and orientation of the wearer, while the last three components are considered noise. External vibrations, such as those felt in an elevator or while driving in a car, are assumed nonexistent. In this work, the TA is to be used either in a clinical or home environment and thus, the assumption is reasonable. Secure placement of the device will limit artifact caused by the device moving while it is worn. It is assumed artifact due to the accidental bumping of the device does not occur. The accelerometers used in the TA have very little noise (approximately 0.14 %FSO). Additionally the error introduced via the conversion from analog to digital is very small. As such, noise intrinsic to the TA is neglected. Thus, the output of the TA is considered to be a sum of the GA and BA components.

3.4.1 The gravitational acceleration component

The GA component of the TA signal is the projection of the earth's gravitational acceleration vector, $\tilde{\boldsymbol{g}}$, onto each of the sensitive axes of the TA's accelerometer. This is shown in figure 3.10, which shows the projection of $\tilde{\boldsymbol{g}}$ onto a sensitive axis, X. If the TA

is stationary, then the output of the TA on the X-axis would be equal to the value of the projection, which is given by –

$$\tilde{\boldsymbol{g}}\boldsymbol{cos}(\Phi) \longrightarrow (\mathbf{1})$$

where Φ is the angle between $\tilde{\boldsymbol{g}}$ and the direction of X. Thus, when a sensitive axis of the TA is aligned parallel with $\tilde{\boldsymbol{g}}$, the output for that axis would register $+1\tilde{\boldsymbol{g}}$. Similarly, when aligned anti-parallel to $\tilde{\boldsymbol{g}}$, the TA would register $-1\tilde{\boldsymbol{g}}$, when aligned orthogonal to $\tilde{\boldsymbol{g}}$, the TA would register $0\tilde{\boldsymbol{g}}$ and varies with (1) as the angle between the direction of X and $\tilde{\boldsymbol{g}}$ changes.

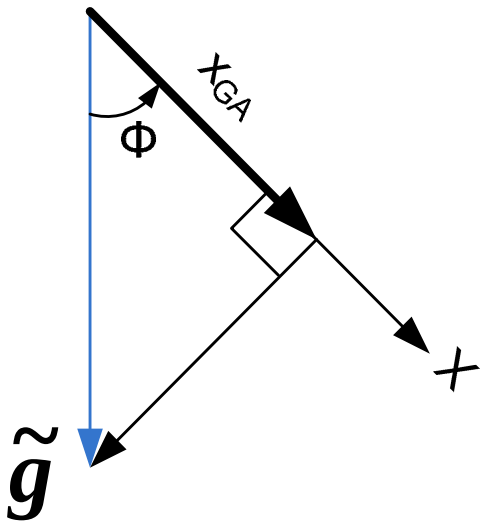


Figure 3.10 - The GA component of acceleration on an accelerometer aligned with X. The GA component, XGA, is the projection of $\tilde{\boldsymbol{g}}$ onto X.

The GA component provides information about the orientation of the TA, relative to $\tilde{\boldsymbol{g}}$, by evaluating the GA components on each of the axes of the TA. This information can be

used to make inferences about the orientation of the user when the placement of the TA on the waist is known. The TA is designed such that the vertical axis of the TA, Z_{TA}, is aligned with $\tilde{\boldsymbol{g}}$ when attached to the waist with the wearer in a standing position. This is shown in figure 9. With this placement of the TA, the tilt angle of the TA, θ, defined as the angle between $\tilde{\boldsymbol{g}}$ and Z_{TA} can be used to define the postural orientation of the wearer. Figure 3.11 illustrates this, using empirically derived thresholds for tilt angle described by Karantonis *et al.* [86]. A tilt angle less than 20 degrees, implies the wearer is standing up. If, $20^o < \theta < 60^o$, the wearers postural orientation is classified as sitting and if $60^o < \theta < 120^o$, the wearers postural orientation is classified as lying. If the exact placement of the TA is known, then the angles between the gravitational vector and X_{TA} and Y_{TA} can be used to determine which side of the body the wearer is lying on. This is illustrated in figure 3.12, in which the TA is placed on the waist at the right anterior iliac crest of the pelvis. At this location, the positive direction of X_{TA} and Y_{TA} are oriented at 45 degrees relative to X_{body} and Y_{body} (see Figure 3.9). It can be seen that each of the four lying sub-postures illustrated, that the orientation of the X and Y axes is sufficient to classify each of the sub-postures. Consider the case when the wearer is lying on their back, X_{TA} and Y_{TA} are both oriented in a negative direction relative to $\tilde{\boldsymbol{g}}$ and thus, would register a GA component < 0 $\tilde{\boldsymbol{g}}$. In the case when the wearer is lying on their left side, X_{TA} is oriented in a positive direction and Y_{TA} is oriented in a negative direction relative to $\tilde{\boldsymbol{g}}$. Thus, the GA component on X_{TA} would be > 0 $\tilde{\boldsymbol{g}}$, while the GA component on Y_{TA} would be < 0 $\tilde{\boldsymbol{g}}$. The GA components on X_{TA} and Y_{TA} when the subject is lying on their front side or right side are opposite to the GA components registered on X_{TA} and Y_{TA} when lying on their back or left side, respectively.

3.4.2 The body acceleration component

The BA component of the TA signal, is the projection of accelerations of the waist, at the location of the TA, onto the sensitive axes, $\{X_{TA}, Y_{TA}, Z_{TA}\}$, of the TA. The BA component characterises the movement of the body, in terms of accelerations measured at a particular point on the waist, relative to the coordinate system established by $\{X_{TA}, Y_{TA}, Z_{TA}\}$. When the TA is not moving or the velocity is constant, the BA component of the TA signal is ideally zero. If the TA moves such that the orientation of the TA remains unchanged relative to $\tilde{\boldsymbol{g}}$, the GA component would remain unchanged and the change in acceleration observed on $\{X_{TA}, Y_{TA}, Z_{TA}\}$ reflects the acceleration caused by the movement of the waist. If on the other hand, the TA moves such that the orientation of the TA relative to $\tilde{\boldsymbol{g}}$ changes, then the GA component and BA component would change simultaneously. The GA component would change in accordance with the change in orientation of the TA. The difference between the GA components and the net acceleration components on $\{X_{TA}, Y_{TA}, Z_{TA}\}$ are the BA components caused by the movement of the waist.

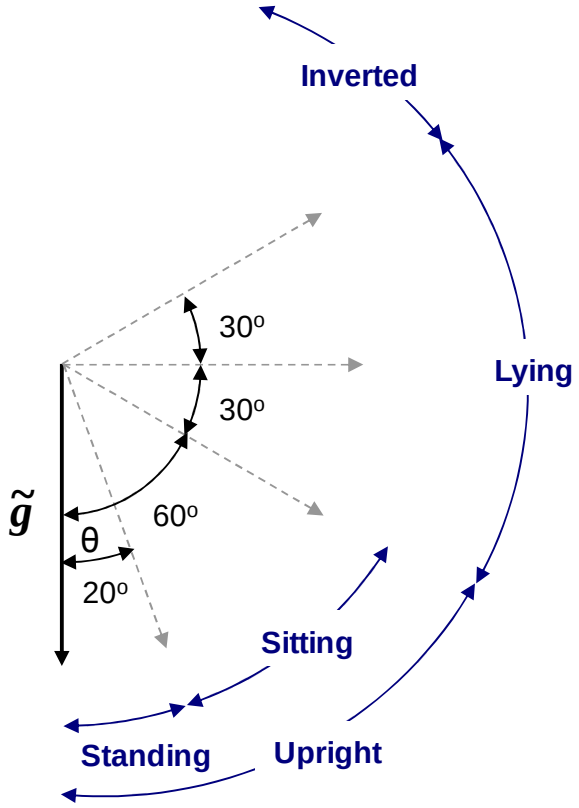


Figure 3.11 - Classification of postural orientation using tilt angle, θ, [86]. The tilt angle is the angle between the vertical axis of the TA and the gravitational vector $\tilde{g}$.

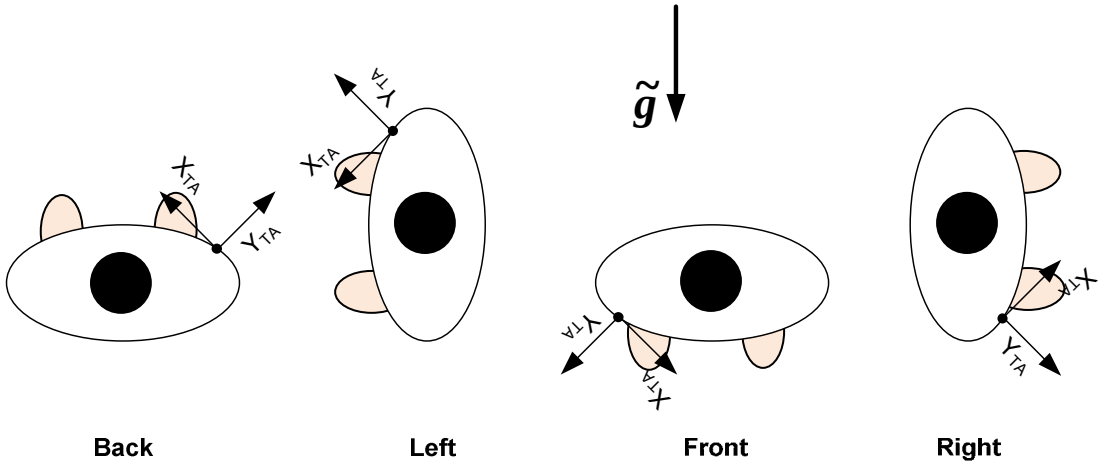


Figure 3.12 - Orientation of the X and Y axes of the TA in each of the four lying substates.

The BA components are a rich form of data that characterise movement of the body at the point of attachment of the TA on the body. A common use of the BA components is in the estimation of energy expenditure [86, 104, 145]. In the context of this thesis, it is hypothesised, that the BA components will contain sufficient information to model falls risk in the elderly and identify physiological deficits.

3.4.3 Separation of acceleration components

As described in the preceding sections, the TA signal is made up of a BA component, relating to the movement of the body, and a GA component which describes the orientation of the TA with respect to the Earth's gravitational vector. At the level of the waist, the TA will be subject to translations and rotations as the body moves. This means the TA will register simultaneous changes in the BA and GA components and thus, the BA and GA components overlap in the time domain. Additionally, the information contained in each component occurs in overlapping frequency spectra. The frequency spectrum of the BA component lies within 0 to 20 Hz, with most of the information contained below 3 Hz. The GA component ranges from 0 to a few hertz [145].

The implication of the BA and GA components overlapping in time and frequency is that approximations must be made, in order to separate the signal and obtain estimates of the BA and GA components. Filtering the raw TA signal to approximately separate the BA and GA components is a well established and accepted method [80, 145-147]. Low-pass filters or high-pass filters with cutoff frequency ranging from 0.1 Hz to 0.5 Hz have been

used to filter out the BA and GA components respectively. Figure 3.13, shows an example using a high-pass filter to obtain the BA component from the raw TA acceleration signal. $x_{raw}[n]$, $y_{raw}[n]$, and $z_{raw}[n]$ are high-pass filtered, at 0.15 Hz [145], to obtain the BA acceleration components $x_{BA}[n]$, $y_{BA}[n]$, and $z_{BA}[n]$. The BA components, subtracted from the raw signal, yields the GA components $x_{GA}[n]$, $y_{GA}[n]$, and $z_{GA}[n]$. In this thesis, a 7-th order Butterworth high-pass filter was used. Matlab's *filtfilt* function is used to provide zero-phase distortion filtering.

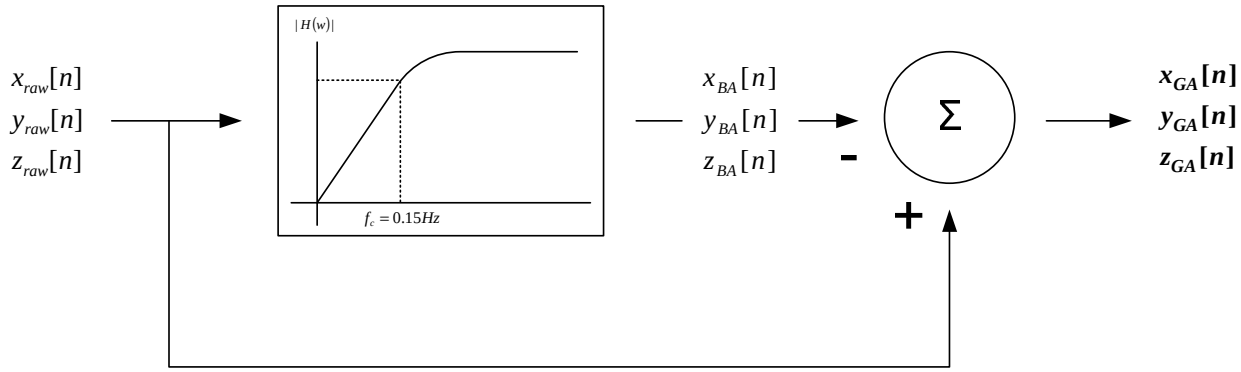


Figure 3.13 - Separation of the GA and BA components from the raw TA signal.

3.5 Chapter conclusion

This chapter presented the requirements and design for a tri-axial accelerometer-based ambulatory monitoring system for the clinical assessment of movement tasks and long-term home monitoring of a controlled movement tasks for the estimation of falls risk in the elderly. The clinical monitoring system, for the supervised assessment of mobility tasks, enables an observer to annotate the collected data with temporal markers to timestamp the various phases of a movement. The home monitoring system implements

the directed routine, a controlled set of movement tasks to be performed unsupervised, using a sequence of audio cues designed to guide the subject through each movement task. Characteristics of the signal obtained via the ambulatory monitor were described in terms of the gravitational and body components of the acceleration signal. The gravitational component describes the orientation of the device and can be used to classify the postural orientation of the wearer. The body acceleration component describes the movement of the device and characterises the movement of the wearer. The following chapter provides the rationale for the unsupervised assessment of falls risk and the methodology for a clinical study to evaluate falls risk in the elderly.

4 Evaluation of falls risk

4.1 Introduction

The primary objective of this thesis is to develop a self-administrable assessment of falls risk for the elderly, using a single, waist-mounted, tri-axial accelerometer. That is, use parameters extracted from movements assessed via the accelerometer to estimate falls risk in the elderly. The aim of making it a self-administrable assessment results in a number of constraints being placed upon the types of movements that can be assessed in an unsupervised setting and the types of parameters that can be extracted from the accelerometer to model falls risk.

This chapter describes the methodology used to evaluate falls risk and provides a detailed rationale for the approach taken, in terms of movement selection and feature extraction. The chapter concludes by describing a clinical study to develop a falls risk model for the elderly.

4.2 Assessing Falls Risk

Falls risk assessment tools come in a variety of forms, from questionnaires, to mobility and balance scales, to complex models of physiological parameters. Whatever the form, there are two fundamental ways in which such assessment tools can been validated.
The first approach is to use a retrospectively collected falls history. Using this history, a hypothesised falls risk assessment can be validated to determine how well it identifies

fallers from non-fallers. However, the validity of this approach hinges on the reliability of the falls history. Studies have shown that ascertaining a falls history from elderly subjects cannot be trusted as it is not reliable [3]. Given a reliable history, a valid assessment tool can be developed to identify fallers from non-fallers. But what is the utility of such an assessment? Given such an assessment is validated against a retrospective history, how well will it predict future fall events?

The second approach involves assessing subjects via some proposed assessment(s) and then prospectively tracking the subjects for a defined period of time to obtain, as reliably as possible, an accurate record of falls. This can be done by using falls calendars or phone interviews for example. Using this reliable falls history, an assessment can be validated (and or developed). The outcome of this approach is a validated falls risk assessment tool that provides, with known sensitivity and specificity, the likelihood of an elderly person falling within a specified time. Such an assessment enables the most efficient means of delivering intervention to the at-risk population.

Such studies are difficult to perform. Apart from devising a neat way to evaluate falls risk, the fundamental challenge lies in obtaining a statistically large enough population of subjects to evaluate and being able to prospectively record fall events as they occur. As such, an alternative approach (and is the approach taken here) is to model an established and prospectively validated assessment tool. While this approach is not ideal in that inaccuracies of the chosen assessment are modelled, it does not detract from the aim of

developing a system to evaluate falls risk in the elderly and highlights the utility of wearable sensors in providing a means of assessing falls risk.

4.3 Assessment of Falls Risk Using an Ambulatory Monitor

Ambulatory monitors, comprising of a variety of sensors, have been used to characterise mobility and functional ability in the elderly (see Section 2.5.2.2). An extraordinarily rich set of parameters can be extracted from such devices and can obviously be used to evaluate falls risk in the elderly. In a prospective cohort study, parameters extracted from assessment using an ambulatory monitor can be used to model falls risk using a prospectively recorded falls history. Using the alternative approach, the cohort of subjects, assessed with the ambulatory monitor, are also assessed using a validated assessment of falls risk. The extracted parameters, from the wearable monitor, are used to model the falls risk scores obtained using the validated falls risk assessment. This is the approach presented in this thesis to develop an assessment of falls risk using a single, waist-mounted ambulatory monitor.

The Physiological Profile Assessment (PPA), described in Chapter 2, is the validated falls risk assessment tool used. The PPA has demonstrated, over a number of validation studies [17], an accuracy of between 75 – 80 % in predicting an elderly person falling within twelve months of being assessed. The PPA is derived from purely objective physiological measures of balance, visual acuity, knee-extension strength, proprioception

and reaction time and does not incorporate subjective or unreliable measures such as falls history or extrinsic environmental factors in estimating one's falls risk.

The fundamental advantage in choosing the PPA, as the gold-standard measure of falls risk, is that it is a validated assessment tool. An additional, and very important advantage, is that the performance across the five physiological tests performed is known and can therefore be modeled using parameters from the ambulatory monitor. Identifying the 'at risk' elderly population is immensely useful, but being able to quantify the factors contributing to one's risk, via models of physiological assessments, provides invaluable information for falls clinics to providing intervention to reduce one's risk of falling.

The PPA falls risk score is calculated as the weighted sum of the standard scores, z_i, for each of the PPA assessments, as shown in equation 1. The weights, ω_i, were obtained using linear discriminant analysis over a large sample of elderly, community-dwelling, population in which falls were monitored via falls calendars [17].

$$Falls\ Risk = w_0 + \sum_{i=1}^{n} \omega_i z_i \qquad -(1)$$

Therefore, the task of modeling the PPA, using a single waist-mounted triaxial accelerometer (TA), reduces to finding a set of parameters that can be extracted from the TA that best characterises the PPA assessment tasks. That is, to find movements from which parameters can be extracted that relate to the performance in the PPA assessments of balance, vision, body sway, proprioception and reaction time.

The choice of movements to assess has a direct bearing on the type of parameters that can be evaluated and thus impacts the performance of any derived models. The following sections provide a general description of the design of the ambulatory monitor used to assess falls risk and evaluates of the considerations that must be made when choosing movements to assess in an unsupervised free-living setting. A number of movements are evaluated and considered for use in an unsupervised assessment.

4.3.1 Controlled directed routine versus uncontrolled free-living data

The aim is to develop an unsupervised assessment of falls risk. That is, an assessment that can be carried out by the user alone and without the need of a care provider assisting them. In this context, there are several constraints placed on the type of movements which can be performed as well as the type of parameters that can be extracted from the TA data.

There are two distinct options for assessment in an unsupervised environment: 1) extract parameters from uncontrolled free-living data, and; 2) extract parameters from controlled free living data. Naturally, each approach has its advantages and disadvantages which need to be considered.

Uncontrolled free-living data is data collected from a person, wearing the TA, as they perform their daily activities. As such, the data typically comprises of periods of sitting, lying, standing and the transitions between these postures, periods of walking and an

inordinate variety of intermediary postures and movements that occur as part of normal daily living.

The primary advantage of this approach is that it is relatively unobtrusive, in that, a user is simply required to wear the device while awake and go about their lives as they normally would and do not have to perform tasks outside of their normal activities. Additionally, the interaction with the device, outside of wearing it, is quite minimal. A user would be required to place the device on the body when they wake up and remove it when they go to sleep. This is beneficial as technology can induce feelings of fear and discomfort in the elderly [104].

A number of disadvantages exist with use of uncontrolled free-living data: 1) the user would have to wear the device daily and for long periods of time to obtain statistically significant data; 2) the context in which the user performs various movements or their orientation in a particular posture needs to be given careful consideration. This is because context drives the way movements are performed. Consider for example, the transition from sit to stand. A sit-to-stand transition from a rigid timber chair would be considerably easier than from a compliant lounge. A less obvious example would be the change in activity as the result of having a visitor. The collected data may show a disproportionate reduction in activity for the day as a result. Without knowing the context in which the movements are performed there is an inherent ambiguity in the collected data. The implication being that more complicated processing of data is required. Finally, a major disadvantage of uncontrolled free-living data is the inability to target particular

physiological deficits. Changes in normal activity are used to infer changes in functional ability and falls risk. It is not possible to explicitly assess particular mobility parameters.

In contrast, controlled free-living data is data collected from a person, wearing the TA, performing a specific movement task or set of movement tasks. For example, a controlled movement would be to have the user perform a sit-to-stand transition as quickly as possible or perform a timed up-and-go test. Mattie *et al.* [104] used this method in a pilot study of free-living activity monitoring and had the participants perform a 'directed routine' of controlled movement tasks in which, the subject, from a seated position, stood up, walked to their bed, lied down and then stood up again. A computer was used to provide instructions to the subjects indicating when to perform each of the directed routine (DR) tasks. Parameters extracted from the DR were used to model the COOP Wonka [106] wellness index.

There are a number of advantages to using controlled DR data. One of the more significant advantages is that the context in which the movements are performed is now controlled as the user is instructed on how and when to perform the task or tasks. In this way, parameters extracted from the collected data can be directly compared from one sample to another and therefore longitudinally. Another significant advantage is the ability to target particular physiological deficits when selecting movement tasks to perform. For example, in order to assess lower-limb strength the user could perform repeated sit-to-stand transitions as quickly as possible or to assess balance the DR could include a stepping test [40]. This allows the DR to potentially evaluate a broad range of

functional ability in the elderly by carefully selecting the DR tasks. In this way, movements can be chosen that would most likely explain the physiological tests used to obtain the falls risk score using the PPA.

In contrast to the collection of uncontrolled free-living data, controlled free-living data would require the user to wear the device only as long as the DR takes to administer. The data for a single DR can be used to evaluate a falls risk score. This means that changes in falls risk can be identified as early as possible. Identifying changes in uncontrolled free-living data would require relatively long periods of data, making it less reactive to changes in falls risk and functional ability.

The main disadvantage in the use of controlled free-living data is the increased interaction between the user and device in order to administer the controlled movement tasks. Additionally, the user is now expected to perform tasks outside of their normal daily routines.

Considering the advantages and disadvantages of each approach, it was concluded that the use of a controlled DR of movement tasks is more appropriate and controllable for the modeling of the PPA falls risk assessment. The reduced complexity and ambiguity of collected data and the advantage of selecting tasks that potentially correlate to the PPA assessment tasks form the basis for selecting the DR approach over modeling uncontrolled free-living data.

4.3.2 Directed Routine Movement Selection

As discussed in the preceding section, a major advantage with controlled free-living data is the potential to tailor a movement, or set of movements, to indirectly evaluate the physiological parameters the PPA assesses. However, the selected movements are constrained by the aim of developing an unsupervised assessment of falls risk.

Safety is paramount in an unsupervised assessment and places a heavy restriction on the type of movements that can be performed. Consider the assessment of postural stability. Body sway measured using a sway meter and by standing as still as possible on a compliant surface is commonly performed in falls clinics [17]. Pseudo-measures of body sway are possible by way of body worn sensors [110-112]. However, without assistance, attempting such a task is extremely risky. As such, movements must be evaluated for safety prior to further consideration.

Complexity of the assessment tasks needs to be considered. If the tasks are too complicated the advantage of control in a DR is somewhat lost as the tasks may become difficult to repeat. Simple movement tasks, that do not involve too many processes, or require much thought to perform, are the most useful and provide the best chance of ensuring compliance with the assessment.

Test/retest reliability is critical when selecting the assessment tasks. A reliable movement is one in which, under a fixed condition, is performed in the same way. That is, if a

person performs a movement task in a particular physiological state, their performance when repeating the same task with the same physiological state should be the same. The reason this is critical is evident when considering the derived models of falls risk or the PPA assessment tasks. Assuming conditions of the selected model are met, than any model derived using the extracted parameters from assessments in which the tasks are unreliable will also be unreliable. Consider a model of falls risk, for example, changes in the estimated falls risk score are not necessarily reflective of changes in falls risk but simply the result of the variance in the assessed tasks. Thus derived models are quite specific to the data set used to evaluate the model. DRs of reliable assessment tasks minimise this problem. Changes in the estimated falls risk score are more likely to be as a result of a change in falls risk, as changes in the performance of any of the assessment tasks relates to a physiological change given the assessments are reliable. This makes the interpretation of longitudinal trends much simpler. In this case, derived models are more general (useful) and less constrained to the data set used to evaluate them.

Duration also needs to be considered when selecting DR assessment tasks. Naturally, the shorter the DR the more likely the user will comply with whatever schedule is prescribed to them. The tradeoff is that the more assessment tasks that are performed the greater the amount of information that can be inferred from the DR. Unfortunately, the more unusable the system will be as it would require significant effort to perform. Thus, movements must be carefully selected to provide as much information as possible, while keeping the total duration of the DR to a minimum.

Targeting is the final consideration made when selecting DR assessment tasks. Targeting refers to selection of movements that relate to a target parameter; in this case, falls risk, by relating to the tasks assessed using the PPA. In the ideal case, parameters extracted from the TA for a DR assessment would completely explain the variability in the PPA assessment tasks resulting in a perfect model of the PPA using the DR. However, given the aforementioned constraints placed on acceptable movements, this becomes quite a difficult task. Additionally, movements can be selected to target deficits outside those evaluated by the PPA and therefore potentially provide additional information that clinicians can use to effectively intervene and reduce ones risk.

4.3.3 Device placement versus feature selection

Consideration must be given to the types of features evaluated from the directed routine movement tasks. Given the aim of developing an unsupervised assessment, strict device placement is not trivial to guarantee. In a clinical setting, correct placement of the device is aided by a clinician. Unsupervised, however, correct placement must be assured by the user.

With strict placement assured, there are no impositions on the type of features that may be extracted. One the other hand, if the placement cannot be assured then the types of parameters that can be evaluated are restricted. Consider the orientation of the device. The projection of the gravitational vector onto each axis of the TA can be used to determine the orientation of the TA. The orientation of the device has been used to

classify posture [86]. The classification is based on the assumption that a vertical orientation equates to an upright orientation. The greater the deviation from a vertical orientation, the greater the lean of the body. If the orientation of the device varies with device placement then such classifications are meaningless. In this way, features that assume a certain placement cannot be used as model features.

Features impervious to variance in device placement should be used to evaluate any models. This helps ensure the model will be robust enough for use in an unsupervised environment.

4.3.4 Directed Routine Movements

4.3.4.1 Sit-to-Stand test

The sit-to-stand (STS) test involves performing an STS transfer. It is defined as the time taken from the initial forward-lean [117] to reaching a standing position. A variant of the STS test involves performing five STS transfers as quickly as possible (STS5) [40]. The task evaluated from the initial forward-lean of the first STS transfer until the final seating after the final STS transfer. Figure 4.1 illustrates the STS. The test is performed with arms folded.

Figure 4.1- The sit-to-stand transfer. Adapted from [68].

The STS has been used as a measure of lower-limb strength, functional mobility, balance, and is incorporated into a number of falls risk assessment tools [148-151] and mobility and balance assessments [152-153]. The STS and STS5 are feasible to perform unsupervised. Both versions are safe and require only a chair to perform. The test is straight forward to perform and thus minimally complex. The STS5 has demonstrated excellent test/re-test reliability and the STS fair to good reliability as measured using interclass correlation coefficients (ICC3,1) [40]. In a study comparing mobility assessments, Teidemann *et al.* [40] observed STS and STS5 average assessment times of 1.02 s and 13.00 s for 225 and 362 subjects respectively. Both tests have sufficiently short administration times making them suitable for an unsupervised assessment.

The biggest advantage of the STS/STS5 assessments is their use as proxy measures for lower-limb strength and balance. The PPA assesses both knee-extension strength and

balance and therefore parameters from the STS tasks have the potential to explain some of the variability in two of the five variables used to evaluate falls risk using the PPA.

4.3.4.2 Alternate Step test

The Alternate Step Test (AST) is performed by alternatively, placing the whole of each foot onto, and off of, a small platform 19 cm high and 40 cm wide as quickly as possible eight times [40]. That is four times with each foot. Figure 4.2 illustrates the AST. The test comprises of four cycles.

Figure 4.2 - The alternate step in which the test subject alternatively place each foot onto and off of a small platform as quickly as possible. Adapted from [68].

The AST requires an ability to shift body weight from one foot to the other and provides a measure of lateral stability [40]. The PPA assesses balance by way of a sway meter attached to the waist with mediolateral and anteroposterior body sway evaluated. As such, the AST may partially explain the variability in balance in the falls risk scores.

The AST requires a single piece of specialised equipment, namely the platform. However, the platform is a trivial piece of equipment and easily supplied. The AST is marginally more complicated to perform than the STS5 but not so complicated that it is difficult to learn. The duration of the AST is quite short. Tiedemann *et al.* [40] found an average assessment time of 11.11 s in a sample of 339 elderly subjects and that, the AST demonstrated excellent test/re-test reliability. The one contentious issue would be that of safety. The AST does challenge one's postural stability through the alternative shifting of one's weight from one foot to the other. However, in consultation with the Falls and Balance Research Group (FBRG) at the Prince of Wales Medical Research Institute (POWMRI), who have assessed a large number of elderly subjects with the AST, it is very unlikely that performing the AST would result in a fall. As such, the AST is considered feasible for use in an unsupervised setting.

4.3.4.3 Timed Up-and-Go Test

The timed up-and-go test (TUGT) is performed as follows. From a seated position, stand, walk three meters, turn around and return to the chair and sit down.

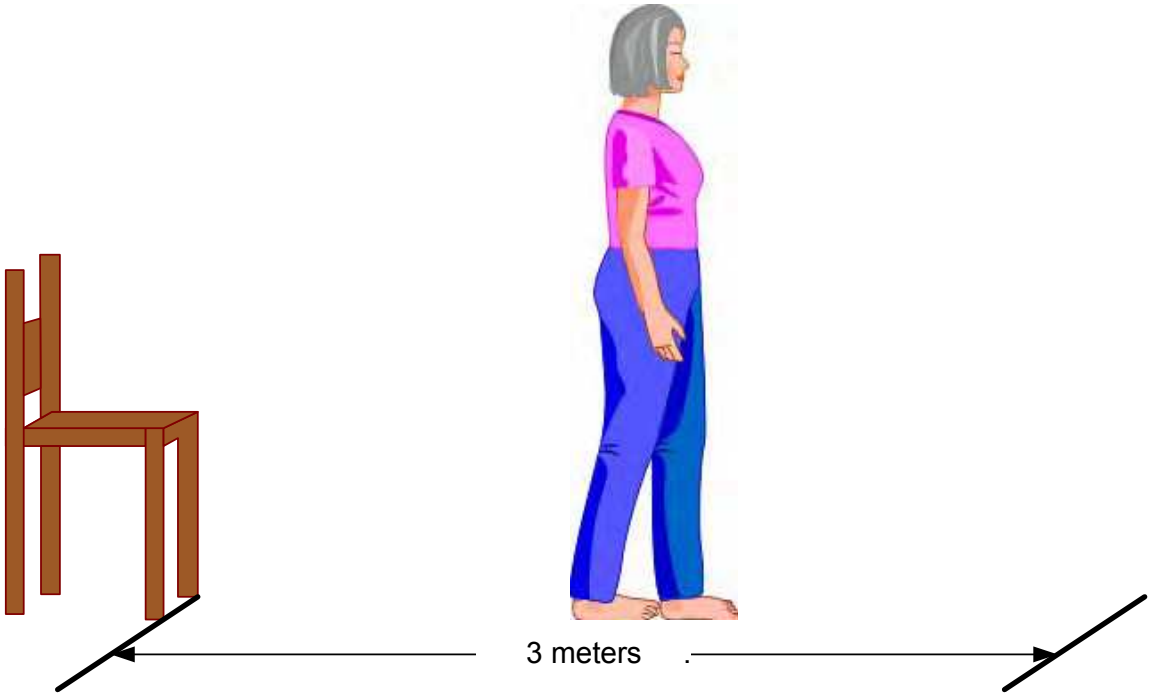


Figure 4.3 - The timed up-and-go test. Adapted from [68].

The TUGT is a well established assessment of mobility in the elderly and has been the focus of a large number of studies. Performance in the TUGT has been shown to significantly correlate with well known mobility indices, such as the Berg Balance test and the Barthel Index [35]. Whitney *et al.* [154], found that the PPA significantly correlates with the PPA falls risk score ($r = 0.39$, $p < 0.0001$), knee extension strength ($r = -0.19$, $p < 0.05$), proprioception ($r = 0.26$, $p < 0.005$), contrast sensitivity ($r = -0.30$, $p < 0.005$) and body sway ($r = 0.31$, $p < 0.001$). Additionally, the TUGT has been recommended by the American and British Geriatric Societies as a screening tool for identifying elderly with an increased risk of falling [1].

The TUGT is a safe test to perform and comprises of movements fundamental to independent living. The TUGT is easy to perform with no complicated maneuvers involved. The TUGT has a relatively short administration time. Whitney *et al.* [154] reported a mean TUGT time of 25.3 s when performing the task at normal pace, while Shumway-Cook *et al.* [37] and Rose *et al.* [38] reported times of 15.3 s and 10.13 s in studies of 30 and 134 elderly subjects, respectively, while performing the TUGT as quickly as possible.

The TUGT is a safe, simple and reliable assessment. Coupled with a short administration time and the relationship with the PPA falls risk and assessment scores the TUGT presents itself as an incredibly useful task to administer.

4.3.4.4 Near-Tandem Standing Balance Test

The near-tandem standing balance (NTSB) test assesses lateral stability for the evaluation of balance in the elderly. The test is performed by standing in the near-tandem position, with arms folded across the chest, with either eyes open or closed for a period of thirty seconds [155]. The near-tandem position involves placing the one foot 2.5 cm anterior and 2.5 cm lateral to the great toe of the second foot [155] as shown in Figure 4.4. The test measures lateral sway using a sway meter attached to the waist and the occurrence of a protective step.

Figure 4.4 - The near-tandem standing balance test. Adapted from [68].

Lord *et al.* [155] found in a study of 156 community-dwelling elderly, fallers had an increased lateral sway when performing the NTSB with eyes open or closed. The study also revealed that impaired lower limb proprioception, quadriceps strength, and reaction time where significant predictors of increased sway in the NTSB with eyes open, and that impaired proprioception and quadriceps strength were the best predictors of a protective step in the NSTB with eyes open. Maintenance of balance is fundamental to avoiding falls and thus any assessment capable of assessing balance would be immensely useful for assessment as part of a DR. Additionally, the strong associations between the NTSB and PPA assessment tasks make it more attractive as a potential DR assessment task.

The NTSB only takes a minute to perform (eyes open and eyes closed) and is obviously sufficiently short in duration to be used in an unsupervised routine. The task is slightly complicated, in that it would take some practice to get used to the near-tandem stance. However, the NTSB does perturb ones balance in the assessment of lateral stability and thus increases the risk that balance could be lost in the administration of the NTSB. The question becomes by how much does it increase the risk of falling? This question was posed to the staff at the FBRG at POWMRI. They noted that while the NTSB does perturb balance, taking a protecting step reflexively corrects this imbalance when balance cannot be maintained and it is unlikely to result in a fall. Nevertheless, it may be an unreasonable risk to perform unassisted?

4.3.4.5 Six-Meter Walk Test

The six-meter-walk test (SMWT) involves walking a distance of ten meters at normal pace in which the time taken to complete the middle six meters is taken as the test parameter [40]. The leading and trailing two meters are used to ensure the walking speed over the six meter test region is as constant as possible by eliminating the initial acceleration and final deceleration.

Tiedemann *et al.* [40] found that using a cut-off point of six seconds for the SWMT discriminated between multiple fallers and non-multiple fallers with reasonable sensitivity and specificity. Additionally, an immense body of work exists evaluating the association between features of gait, such as stride time variability and stride length with functional ability and falls in the elderly [40, 156-157]. Hausdorff *et al.* [156] found that

gait stride time variability predicted falls and was significantly correlated with strength, balance, gait speed and functional status in the elderly. Similarly, Maki [157] observed increases stride-to-stride variability in stride length, speed and double support predicted fallers. Thus, there is potential for a variety of parameters can be extracted from an assessment of gait in addition to duration.

Naturally, the SMWT is a simple test to perform and requires no specialised equipment. Tiedemann *et al.* [40] found, for a cohort of 362 elderly subjects, that the SMWT took on average 5.93 s to perform and demonstrated reasonable reliability. However, the limiting factor when considering the feasibility for use in an unsupervised assessment is, whether it is safe to assume ten meters of clear walking space would be available in all settings that the DR assessment is expected to be carried out. Unfortunately, given the wide range in the size of homes, it is unreasonable to assume such space would be available.

4.3.4.6 Half-Turn Test

The half-turn test (HTT) is performed by taking a few steps and then turning around to face the opposite direction. The number of steps taken to complete the turn is taken as the test parameter [40].

The ability to turn around has been used to assess mobility and balance [35, 153]. Tiedemann *et al.* [40] found the HTT to have excellent reliability, but had limited ability in discriminating between fallers and non-fallers. However, given the simple nature of the

test and its short administration time it is very feasible for use in an unsupervised assessment.

4.4 Evaluation of Falls Risk – A Clinical Study

The aim is to develop a simple, self-administrable assessment of falls risk in the elderly. This section describes a clinical study used to develop a model of falls risk and functional ability in the elderly. The study was conducted with the aid of the Falls and Balance Research Group at the Prince of Wales Medical Research Institute (Sydney Australia). The University of New South Wales (Sydney, Australia) ethics committee approved the study and informed consent was obtained from each participant in the study. The participation information statement and consent forms are included in the Appendix A.1.

Participants able to perform the PPA were considered. No additional exclusion criteria used.

4.4.1 Method

Subjects are evaluated for falls risk, using the PPA, followed by an assessment of mobility using the TA and a DR of the AST, TUGT and STS5. Features extracted from the DR data are used to model the PPA falls risk score and PPA assessment tasks.

4.4.1.1 Evaluation of falls risk

Each subject is evaluated for falls risk using the short-form version of the PPA [17]. Subjects perform five physiological tests to evaluate body sway, proprioception, visual acuity, via the Melbourne Edge Test (MET), knee-extension strength and reaction time. The scores in each test are converted to standard scores (z-score) using a large database of test scores for elderly subjects. The standard scores are weighted and summed using the PPA falls risk model to obtain the falls risk score.

In addition to the falls risk score the following data is collected for each subject: Age, sex, MET score, MET z-score, proprioception score, proprioception z-score, knee-extension strength score, knee-extension strength z-score, mean reaction time, reaction time z-score, anteroposterior body sway, mediolateral body sway, body sway z-score, falls history (prospectively recorded) and use of multi-focal eye glasses.

4.4.1.2 Evaluation using the DR and TA

Having been assessed for falls risk, subjects were evaluated using the TA and the selected DR (AST, TUGT and STS5). Subjects were shown how to place the device on their waist and asked to do so themselves. Subjects, who did not have a means of affixing the device to their waist, by either attaching the device to their pants or belt, were provided with a Velcro belt.

Each assessment task was described and demonstrated to the subjects prior to performing the task. The following instructions were given to the subjects for the tasks. For the AST, the subjects were told, “When I say go, alternately place the whole of each foot onto and off of the platform as quickly as possible eight times. Four times with each foot.”. For the TUGT the subjects were told, “When I say go, stand, walk to the three meter mark, turn around, walk back to the chair and sit down. Perform the task as quickly as possible.”. For the STS5, the subjects were told, “When I say go, perform five sit-to-stand transfers as quickly as possible.”.

Figure 4.5 shows the setup for the TUGT. A distance of three meters was marked using tape and a chair placed at one end.

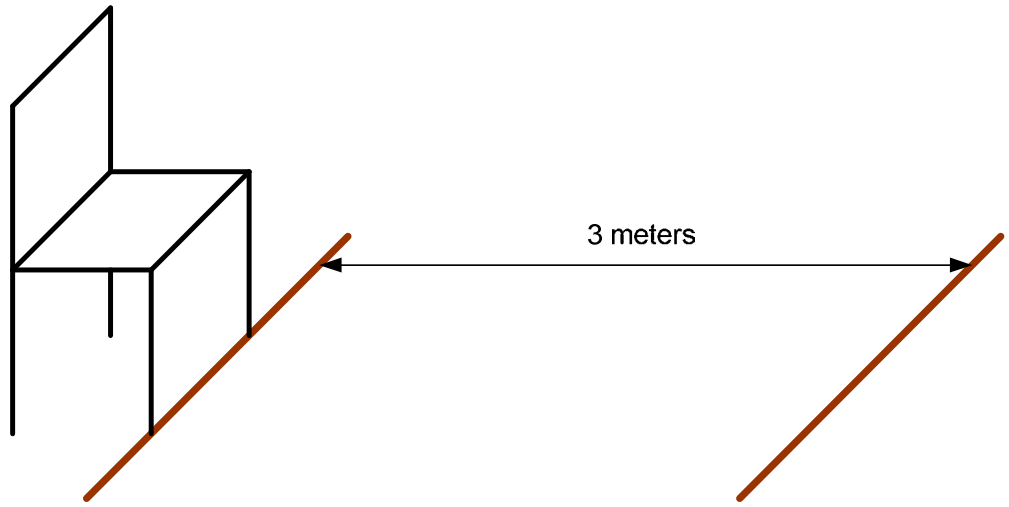


Figure 4.5 - TUGT test setup

Figure 4.6 shows the experimental setup using the TUGT as an example. The TA streams, in real-time, the sampled acceleration data. Data is transmitted sample-by-

sample over the Bluetooth link to a laptop running a custom data collection tool that allows temporal markers to be inserted into the data stream by pressing the annotation button. The markers are used to define the start and end times the tasks as well as mark the intermediate phases of each task. For the AST, the start and end times are marked as well as the AST cycle times by marking the time when each foot touches the ground. For the TUGT, the start and end times are marked as well as the time the subject reaches a standing position, reaches the three meter mark, completes the turn, reaches the chair and completes the stand-to-sit transfer. For the STS5, the start and end times are marked as well as the cycle times by marking the start times for each sit-to-stand transfer. Figures 4.7-4.9 show representative examples of the observer marked recording for the AST, TUGT and STS5, respectively.

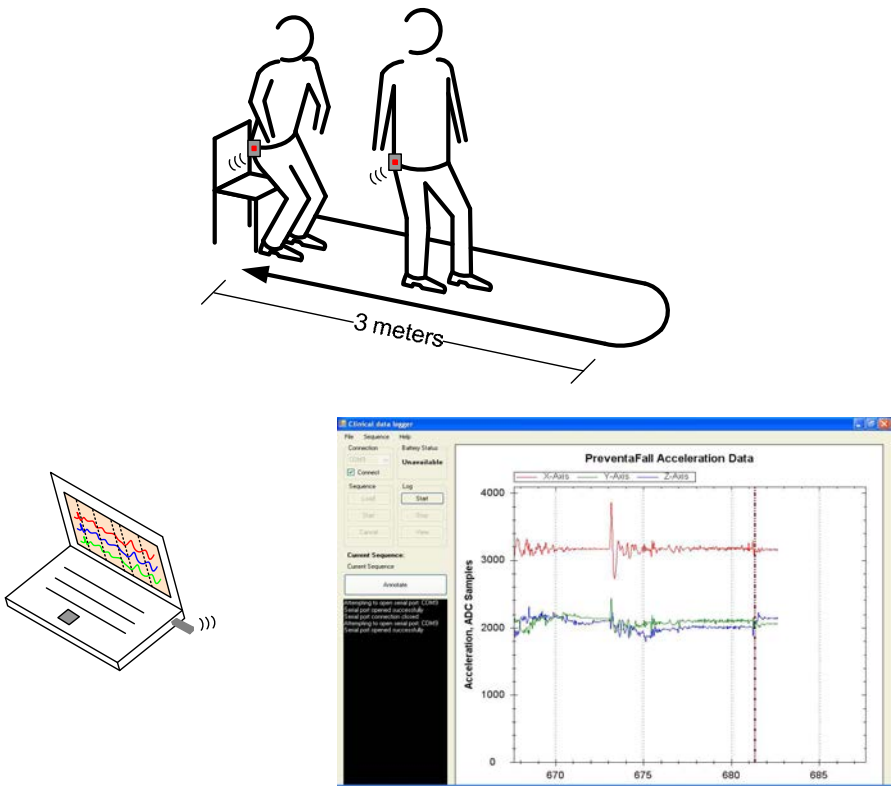


Figure 4.6 - DR experimental procedure for the TUGT.

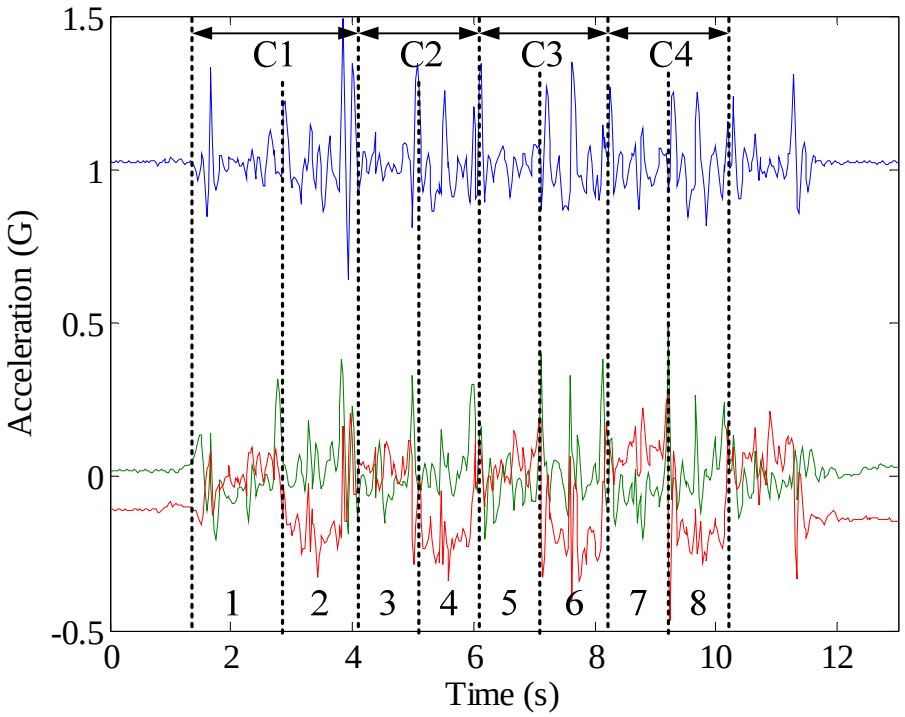


Figure 4.7 - Representative, manually annotated TA data for the AST.

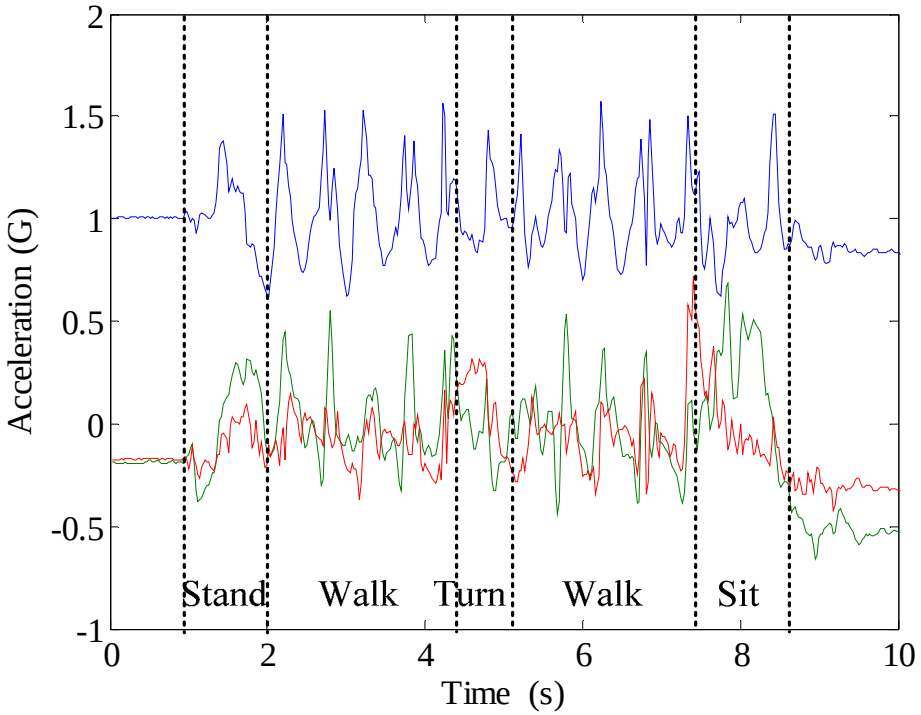


Figure 4.8 - Representative, manually annotated, TA data for the TUGT.

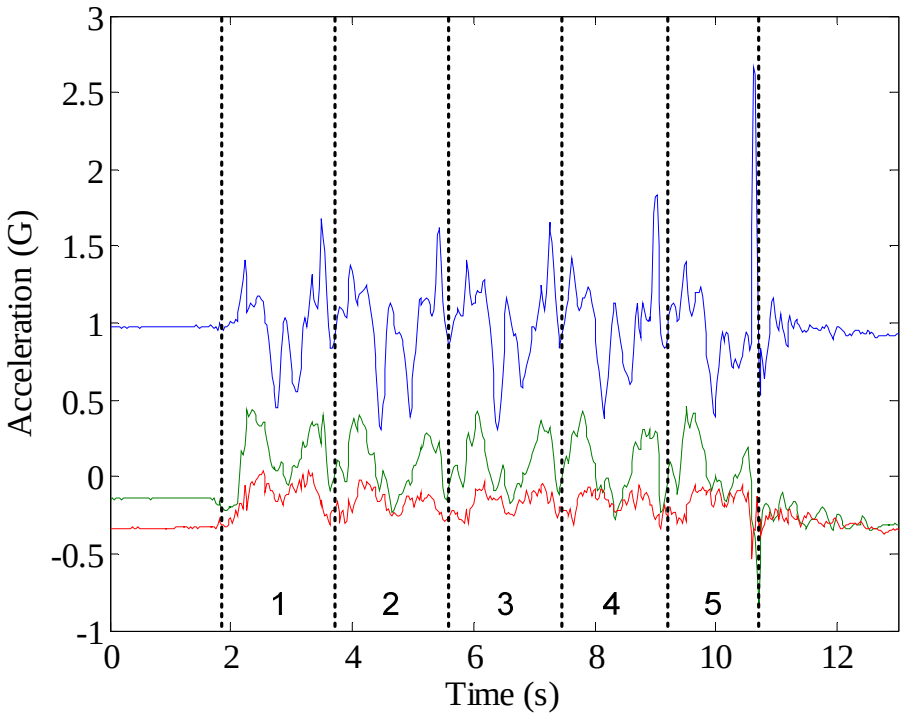


Figure 4.9 - Representative, manually annotated, TA data for the STS5.

4.4.1.3 Feature Extraction

The DR data is processed to obtain a set of features to model falls risk and the PPA assessment tasks. The manually inserted markers are used to segment the TA data for each task and provides a simple means to evaluate features for each phase of a DR task. Given the subjects place the device onto their own waists, features must be robust enough to handle variation in the placement of the device and should not rely on a particular orientation of the device. Signal processing and modeling was performed using Matlab®.

4.4.1.4 Modeling of Falls Risk and Functional Ability

Linear least squares models are used to evaluate falls risk and functional ability from a set of features, extracted from the DR data, against the falls risk scores and PPA assessment task scores obtained during the assessment of falls risk. For *N* subjects and a set of *M* features for example, a matrix ***X***, defined as:

$$X = \begin{pmatrix} f_{11} & f_{12} & f_{13} & . & . & . & f_{1M} & 1 \\ f_{21} & f_{22} & f_{23} & . & . & . & f_{2M} & 1 \\ f_{31} & f_{32} & f_{33} & . & . & . & f_{3M} & 1 \\ . & . & . & . & & & . & . \\ . & . & . & & . & & . & . \\ . & . & . & & & . & . & . \\ f_{N1} & f_{N2} & f_{N3} & . & . & . & f_{NM} & 1 \end{pmatrix}$$

contains *N* rows of *M* features augmented with a column of ones (to resolve the model constant term), evaluated from the DR data. Each row represents the *M* features extracted for an individual from their DR assessment data. A target vector, ***b***, can be defined as:

$$b = \begin{pmatrix} b_1 & b_2 & b_3 & . & . & . & b_N \end{pmatrix}^T$$

where *T* represents the matrix transpose and b_i the target value to be modeled for the i^{th} subject. The target vector could be the falls risk scores obtained from the PPA or in the individual PPA assessment scores. A linear least squares model, looks to find the weights, *w*, where:

$$w = \begin{pmatrix} w_1 & w_2 & w_3 & . & . & w_M & w_{M+1} \end{pmatrix}^T$$

that minimises the root-mean-squared-error (RMSE),

$$RMSE = \left(\frac{1}{N} \left(\sum_{i=1}^{N} \left(b_i - \hat{b}_i \right)^2 \right) \right)^{\frac{1}{2}} \qquad -(2)$$

between the true target values, b, and the estimate of the target values, $\hat{b}$, where,

$$\hat{b}_i = w_{M+1} + \sum_{j=1}^{M} w_j \cdot f_{ij} \qquad -(3)$$

The weights, w, are resolved using the following relationship,

$$w = X^{+} b \qquad -(4)$$

A feature selection algorithm is used to try and find an optimal subset of features, from the overall feature pool, for each of the derived models. Figure 4.10 shows a flowchart of the sequential forward floating search (SFFS) [158] feature selection algorithm that attempts to find the optimal subset of features. The algorithm takes a bottom up approach by starting with an empty set of selected features and the unselected feature set equaling the entire feature pool. While the feature search yields improvements in model performance, each feature in the unselected feature set is considered for inclusion in the selected set of features. The model is evaluated using the selected set of features plus the new feature being considered. The feature that most improves the RMSE of the model is added to the selected set of features. After this forward search, features from the selected set of features are considered, one at a time, for removal from the selected set of features The feature that most improves the RMSE of the current model is removed from the selected set of features. This process of adding and removing features from the selected set of features continues until the model performance converges and no further improvements can be found.

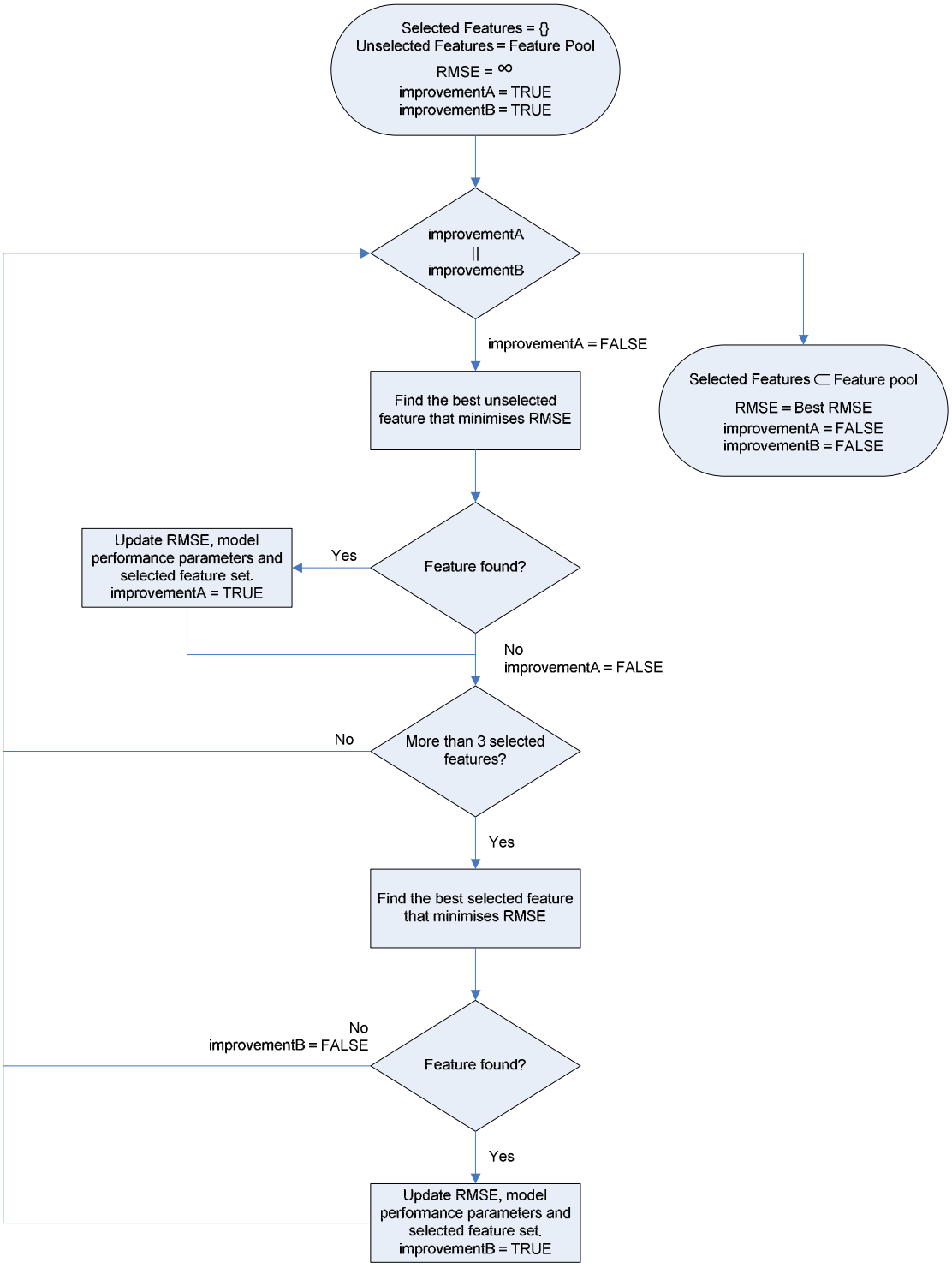


Figure 4.10 - Feature selection algorithm

Leave-one-out cross-fold validation is used to provide an unbiased evaluation of the RMSE of the trained models. This involves removing the data for i^{th} subject from the matrix **X** and **b** by removing the i^{th} row. The model is trained using the remaining data and the estimate of falls risk calculated using the resolved weights and Equation 3. This is repeated for each of the N subjects. Once the N estimates are obtained the RMSE is calculated using Equation 2.

Using this technique models for falls risk (FR), knee-extension strength (KES), body sway (BS), the Melbourne Edge Test (MET) and proprioception (PROP) are evaluated. So, for a set of features, $F = \{f_1, f_2, ..., f_n\}$, extracted from the TA data,

$$FR = w_{k+1} + \sum_{j=1}^{k} w_j \cdot r_j \quad where, \; R = \{r_1, r_2, ..., r_k\} \subset F$$

$$KES = l_{p+1} + \sum_{j=1}^{p} l_j \cdot q_j \quad where, \; Q = \{q_1, q_2, ..., q_p\} \subset F$$

$$BS = g_{s+1} + \sum_{j=1}^{s} g_j \cdot t_j \quad where, \; T = \{t_1, t_2, ..., t_s\} \subset F$$

$$MET = d_{i+1} + \sum_{j=1}^{i} d_j \cdot y_j \quad where, \; Y = \{y_1, y_2, ..., y_i\} \subset F$$

$$PROP = e_{a+1} + \sum_{j=1}^{a} e_j \cdot h_j \quad where, \; H = \{h_1, h_2, ..., h_k\} \subset F$$

R, *Q*, *T*, *Y*, and *H*, subsets of the total feature pool, *F*, are those obtained using the feature selection algorithm shown in Figure 4.10. *w*, *l*, *g*, *d*, and *e* are the linear least squares model weights obtained using Equation 4.

4.5 Conclusion

This chapter described the methodology for the evaluation of falls risk in the elderly using an ambulatory monitor. Considerations and constraints on the type of movements that can be evaluated unsupervised were described. Free-living ambulatory data, which requires the user to wear the device throughout the day, was compared with controlled movements (the directed routine) that require the user to perform explicit movement tasks. Controlling unsupervised movements provides the greatest flexibility to target movements toward particular risk factors for falls that will assist in the estimation of falls risk. The safety, feasibility and potential targeting of a set of candidate movement tasks were described. A directed routine consisting of the AST, TUGT and the STS5 was selected for evaluation in a clinical study to evaluate falls risk in the elderly. Falls risk and falls risk factor models are derived from features extracted from the AST, TUGT and STS5 evaluated using the ambulatory monitor attached to the waist. The following chapter describes the analysis of the AST, TUGT and STS5 data, to extract a set of candidate features to model falls risk and physiological function.

5 Directed Routine Analysis

5.1 Introduction

A cohort (N=68) subjects were assessed for falls risk at the Prince of Wales Medical Research Institute, Sydney, Australia. The cohort was also assessed, via the TA, while performing a set of controlled movement tasks, the DR. Each subject performed the DR once. The aim is to develop an unsupervised assessment of falls risk. As described in Chapter 4, features extracted from the DR acceleration data are to be used to model falls risk and functional ability, by developing linear least-squares models that map the extracted features to the falls risk and/or the PPA mobility task scores.

This chapter describes the processing of the DR data to extract features in order to model falls risk and functional ability. The features extracted, are constrained by expected variation in the placement of the TA on the body in an unsupervised assessment, as the wearer must place the TA onto their waist, unassisted. The implication is that extracted features should be robust enough to handle variation in the placement of the TA and should not rely on the strict placement of the device. Simple temporal parameters, extracted using the annotations inserted by an observer of the DR, and signal energy estimates comprise the bulk of the features extracted. An estimate of the stepping frequency, for the walking phases of the TUGT, is calculated. Additionally, a dissimilarity metric is defined to assess the repeatability of the quasi-periodic STS5 and AST DR assessments. The processing is described below for the TUGT, AST and STS5 in turn.

5.2 The Timed Up-and-Go Test

The TUGT is performed by standing from a seated position, walking three meters in a straight line, turning around, walking back to the chair and sitting down. It is performed as quickly as possible. Subjects were allowed to use their arms. Figure 5.1, shows a representative sample of the TUGT as evaluated by the TA. Six markers, $\{m_1, m_2, ..., m_6\}$, are placed by an observer and represent the start time (m_1), the time at which the subject is standing upright (m_2), the time the subject reaches the three meter mark (m_3), the time at which the subject completes the turn (m_4), the time at when the subject reaches the chair (m_5) and the time when the subject completes the stand-to-sit transfer (m_6) respectively.

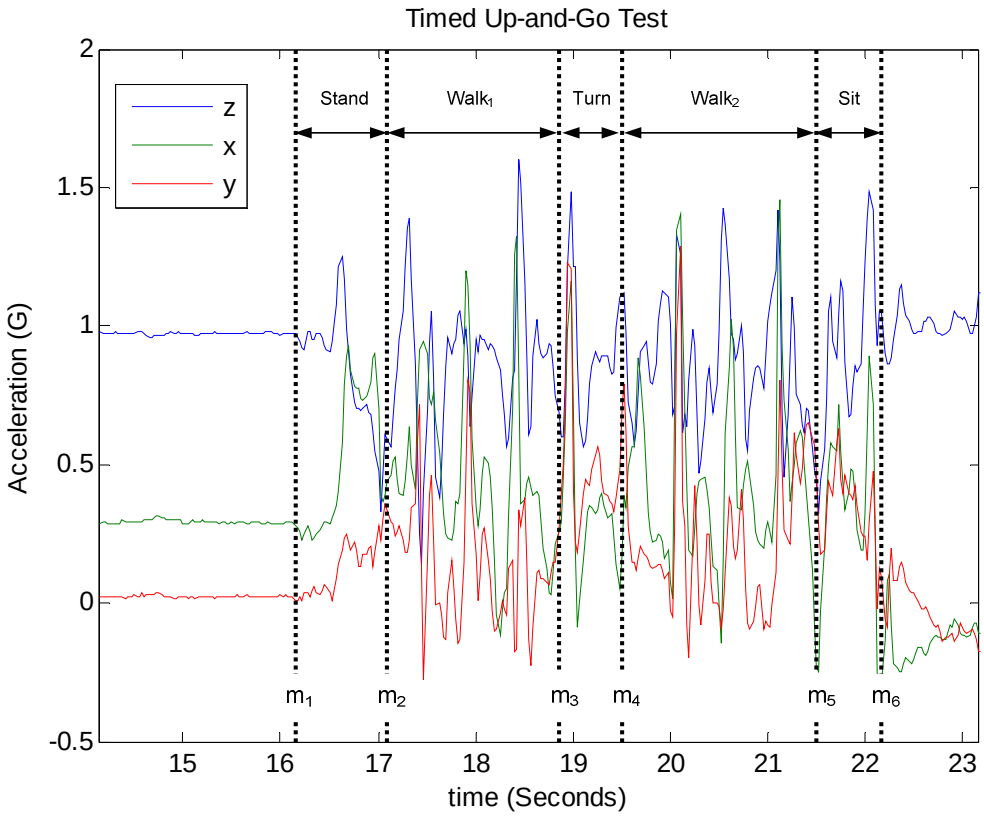


Figure 5.1 - Representative TUGT acceleration data showing the TUGT phases and observer annotations {m1, m2,…, m6}

5.2.1 Temporal Parameters

The observer placed markers, $\{m_1, m_2, ..., m_6\}$, are used to extract the following temporal parameters for the TUGT:

$$TUGT_{Duration} = m_6 - m_1 \quad = \quad Time\ to\ complete\ the\ TUGT \quad \longrightarrow \quad (f_1)$$
$$TUGT_{Stand} = m_2 - m_1 \quad = \quad Time\ taken\ to\ stand\ up \quad \longrightarrow \quad (f_2)$$
$$TUGT_{3m} = m_3 - m_2 \quad = \quad Time\ taken\ to\ walk\ 3m \quad \longrightarrow \quad (f_3)$$
$$TUGT_{Turn} = m_4 - m_3 \quad = \quad Time\ taken\ to\ turn\ around \quad \longrightarrow \quad (f_4)$$
$$TUGT_{Chair} = m_5 - m_4 \quad = \quad Time\ taken\ to\ walk\ to\ the\ chair \quad \longrightarrow \quad (f_5)$$
$$TUGT_{Sit} = m_6 - m_5 \quad = \quad Time\ taken\ to\ sit\ down \quad \longrightarrow \quad (f_6)$$

In addition to the basic timing features, $\{f_1, f_2, ..., f_6\}$, an estimation of the stepping frequency during the walking phases of the TUGT ($Walk_1$ and $Walk_2$) is evaluated. The estimate of stepping frequency is derived from BA components, $x_{BA}[n]$, $y_{BA}[n]$ and $z_{BA}[n]$, of the measured acceleration data for the TUGT, $x_{Raw}[n]$, $y_{Raw}[n]$ and $z_{Raw}[n]$ (see Section 3.4.2). The BA components are used to evaluate the signal vector magnitude (SVM) where,

$$SVM[n] = \left(x_{BA}[n]^2 + y_{BA}[n]^2 + z_{BA}[n]^2 + \right)^{\frac{1}{2}}$$

The SVM is the magnitude of the acceleration vector at a particular sample point. Figure 5.2 shows the SVM for the representative TUGT shown in Figure 5.1.

The SVM signal is low-pass filtered using a 10th order Butterworth filter with a cut-off frequency of 2.0 Hz (an estimate of the maximum step-rate), to obtain $s[n]$, from which, the estimate of stepping frequency is evaluated. Figure 5.3, shows a block diagram of the preprocessing performed on the TUGT acceleration data to obtain $s[n]$. Figure 5.4, shows $s[n]$ evaluated for the representative TUGT data shown in Figure 5.1.

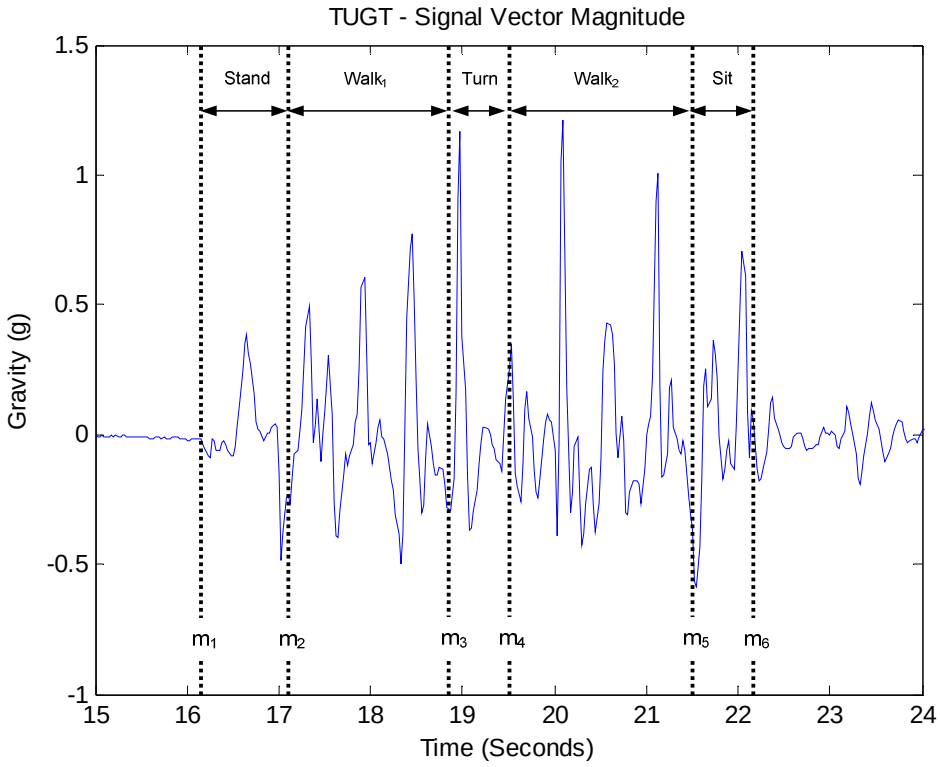


Figure 5.2 - SVM for the representative TUGT shown in Figure 5.1.

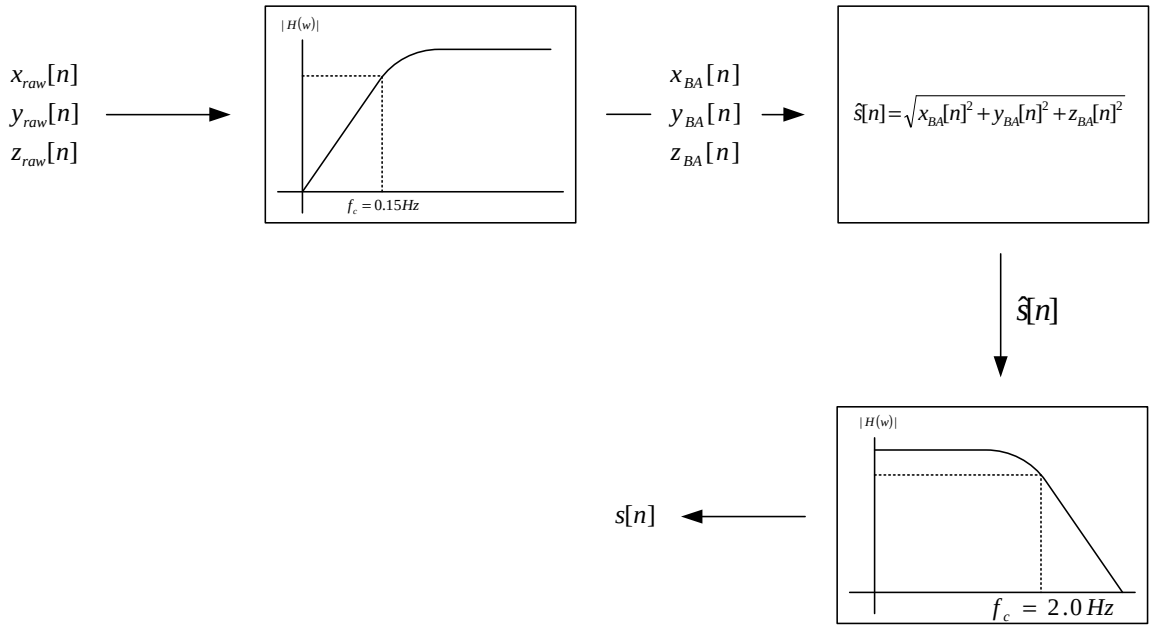


Figure 5.3 - Preprocessing of TUGT data for the estimation of stepping frequency.

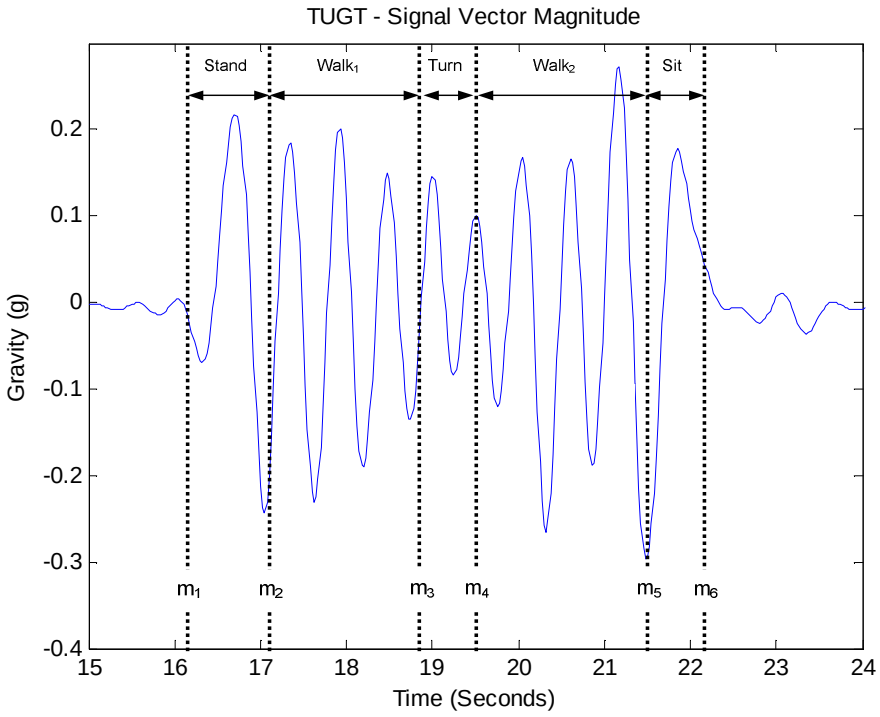


Figure 5.4 - Signal vector magnitude for the TUGT sample shown in figure 5.1.

The number of local maximum in $s[n]$, during the walking phases of the TUGT ($Walk_1$ and $Walk_2$), divided by the duration of the walking phases, is used as the estimate of stepping frequency. That is,

$$f_{STEP} = \frac{N}{TUGT_{3m} + TUGT_{CHAIR}} \longrightarrow (f_7)$$

where N is the number of maximum during found in the segments $Walk_1$ and $Walk_2$ of the TUGT and $TUGT_{3m}$+$TUGT_{CHAIR}$ equals the duration of the walking periods.

The first derivative of $s[n]$, $s'[n]$, is used to find the number of maxima. Suppose that at sample $n = n_0$, $s'[n]$ satisfies the conditions:

$$s'[n_0] = 0$$
$$s'[n_0 - 1] > 0 \; and \; s'[n_0 + 1] < 0$$

then n_0 is a maxima. This process is illustrated in Figure 5.5 which shows a sample of $s'[n]$ including three zeroes. At the first zero crossing, $s'[n]$ is less than zero just before the zero crossing and greater than zero just after, thus a minima. At the second zero crossing however, $s'[n]$ is greater than zero just before the zero crossing and less than zero just after. Therefore, a maxima.

Figure 5.6 shows an example of the estimation using the representative TUGT sample shown in Figure 5.1. In this example, seven maxima are found in the $Walk_1$ and $Walk_2$ phases of the TUGT (see Figure 5.1). The walking phases lasted 3.75 s which yields an estimated stepping frequency of 1.87 Hz.

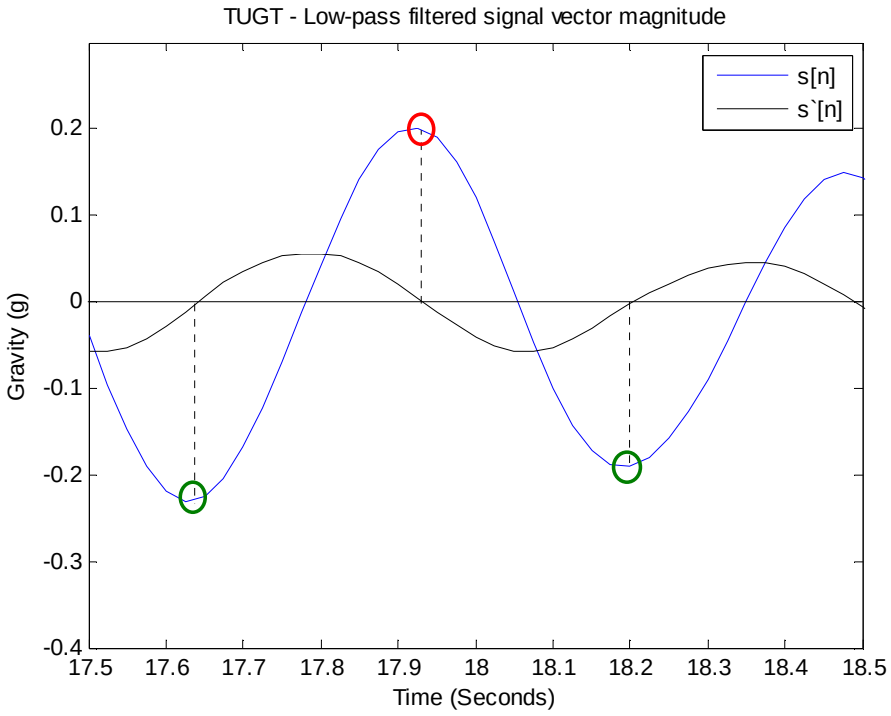


Figure 5.5 - Finding maxima in s[n].

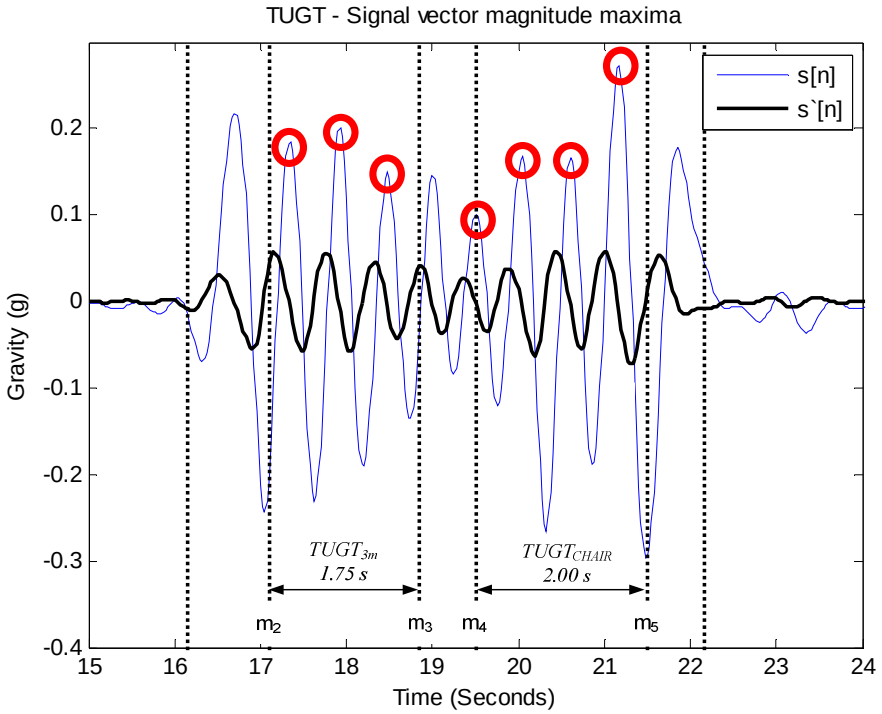


Figure 5.6 - Evaluation of stepping frequency.

5.2.2 Energy Parameters

The body acceleration components $x_{BA}[n]$, $y_{BA}[n]$ and $z_{BA}[n]$ are used to extract a number of energy based parameters from the TUGT. These are based on the signal vector magnitude (SVM) derived as:

$$SVM[n] = \left(x_{BA}[n]^2 + y_{BA}[n]^2 + z_{BA}[n]^2\right)^{\frac{1}{2}}$$

and the signal magnitude area (SMA) derived as:

$$SMA = \sum_{i=j}^{k} \left|x_{BA}[i]\right| + \left|y_{BA}[i]\right| + \left|z_{BA}[i]\right|$$

Which is the discrete integral of the signal magnitude (SM) from sample *i* to *k*, where:

$$SM[n] = \left|x_{BA}[n]\right| + \left|y_{BA}[n]\right| + \left|z_{BA}[n]\right|$$

As an example, consider the body acceleration components $x_{BA}[n] = \{1,0,-1,2,1\}$, $y_{BA}[n] = \{1,2,1,2,1\}$ and $z_{BA}[n] = \{-1,-2,-1,0,1\}$ as shown in Figure 5.7. The signal magnitude is thus, $SM[n] = \{3,4,3,4,3\}$ which gives a SMA of 17 g and is the area under the signal magnitude curve shown in Figure 5.7. The SMA has been shown to estimate the metabolic energy expenditure [80, 145-147].

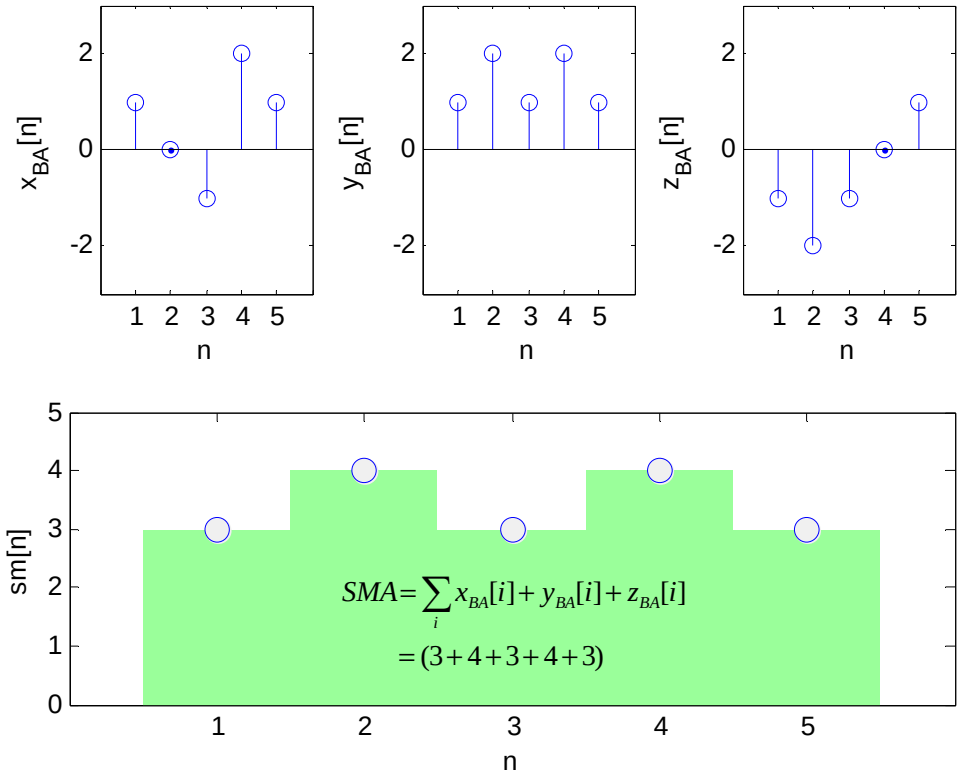


Figure 5.7 - Calculation of SMA.

The SMA and SVM magnitude are used to extract the following TUGT features:

$$TUGT_{SVM\ RMS} = \sqrt{\frac{1}{m_6 - m_1}\sum_{i=m_1}^{m_6} SVM[i]^2} \longrightarrow (f_8)$$

$$TUGT_{SMA} = \sum_{i=m_1}^{m_6} |x_{BA}[i]| + |y_{BA}[i]| + |z_{BA}[i]| \longrightarrow (f_9)$$

$$TUGT_{SMA\ Stand} = \sum_{i=m_1}^{m_2} |x_{BA}[i]| + |y_{BA}[i]| + |z_{BA}[i]| \longrightarrow (f_{10})$$

$$TUGT_{SMA\,3m} = \sum_{i=m_2}^{m_3} |x_{BA}[i]| + |y_{BA}[i]| + |z_{BA}[i]| \longrightarrow (f_{11})$$

$$TUGT_{SMA\,Turn} = \sum_{i=m_3}^{m_4} |x_{BA}[i]| + |y_{BA}[i]| + |z_{BA}[i]| \longrightarrow (f_{12})$$

$$TUGT_{SMA\,Chair} = \sum_{i=m_4}^{m_5} |x_{BA}[i]| + |y_{BA}[i]| + |z_{BA}[i]| \longrightarrow (f_{13})$$

$$TUGT_{SMA\,Sit} = \sum_{i=m_5}^{m_6} |x_{BA}[i]| + |y_{BA}[i]| + |z_{BA}[i]| \longrightarrow (f_{14})$$

f_8 is the root-mean-squares (RMS) SVM for the TUGT and relates to the RMS force for the TUGT measured the level of the waist. f_9 is the estimate for the total energy expended during the TUGT while $\{f_{10},f_{11},\ldots,f_{14}\}$ are the estimates for the energy expended during each phase of the TUGT.

5.3 The Alternate Step Test

The AST involves alternately placing the whole of each foot onto and off of a small platform 19 centimeters high and 40 centimeters wide, as described by Tiedemann *et al.* [40]. Figure 5.8 shows a representative example of the AST. The figure plots the raw acceleration data, as measured by the TA. Nine markers, $\{m_1, m_2, ..., m_9\}$, are placed by an observer marking the start time and the times at which each foot is returned to the ground.

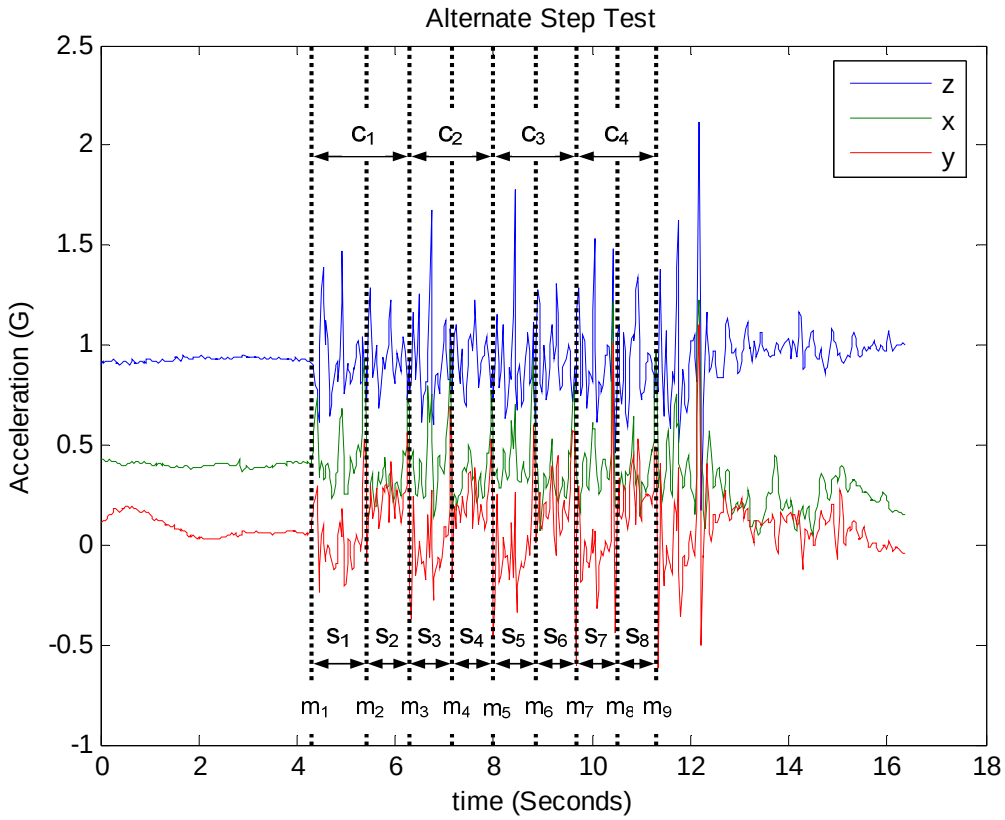


Figure 5.8 - Representative AST recording showing markers, step times and cycle times.

5.3.1 Temporal Parameters

The nine AST markers are used to define a number of temporal features. Consider the sequence, $d[i] = \{d_1, d_2, ..., d_n\}$, which represents the sampled TA data for the AST. The following segments, which are illustrated in Figure 5.8, are used to define the parameters:

$$
\begin{aligned}
S_1 &= d[i] \ for \ m_1 \le i \le m_2 \\
S_2 &= d[i] \ for \ m_2 < i \le m_3 \\
S_3 &= d[i] \ for \ m_3 < i \le m_4 \\
S_4 &= d[i] \ for \ m_4 < i \le m_5 \\
S_5 &= d[i] \ for \ m_5 < i \le m_6 \\
S_6 &= d[i] \ for \ m_6 < i \le m_7 \\
S_7 &= d[i] \ for \ m_7 < i \le m_8 \\
S_8 &= d[i] \ for \ m_8 < i \le m_9 \\
C_1 &= d[i] \ for \ m_1 \le i \le m_3 \\
C_2 &= d[i] \ for \ m_3 < i \le m_5 \\
C_3 &= d[i] \ for \ m_5 < i \le m_7 \\
C_4 &= d[i] \ for \ m_7 < i \le m_9
\end{aligned}
$$

S_1, S_3, S_5 and S_7 are the segments of data for the leading-foot steps. That is, the segments with the foot used to take the first step. S_2, S_4, S_6 and S_8 are the segments of data for the trailing-foot steps. That is, the segments with the foot used to take the second step. Steps one and two (S_1 and S_2) form the first AST cycle. Similarly, S_3 and S_4, S_5 and S_6 and S_7 and S_8 form AST cycles two, three and four respectively. Via the observer placed markers, the following temporal features for the AST are extracted:

$$AST_{Duration} = m_9 - m_1 \quad = \quad Time\ to\ complete\ the\ AST \quad \longrightarrow \quad (f_{15})$$

$$AST_{t1} = m_2 - m_1 \quad = \quad \textit{Time to complete the first step} \quad \longrightarrow \quad (f_{16})$$

$$AST_{t2} = m_3 - m_2 \quad = \quad \textit{Time to complete the second step} \quad \longrightarrow \quad (f_{17})$$

$$AST_{t3} = m_4 - m_3 \quad = \quad \textit{Time to complete the third step} \quad \longrightarrow \quad (f_{18})$$

$$AST_{t4} = m_5 - m_4 \quad = \quad \textit{Time to complete the fourth step} \quad \longrightarrow \quad (f_{19})$$

$$AST_{t5} = m_6 - m_5 \quad = \quad \textit{Time to complete the fifth step} \quad \longrightarrow \quad (f_{20})$$

$$AST_{t6} = m_7 - m_6 \quad = \quad \textit{Time to complete the sixth step} \quad \longrightarrow \quad (f_{21})$$

$$AST_{t7} = m_8 - m_7 \quad = \quad \textit{Time to complete the seventh step} \quad \longrightarrow \quad (f_{22})$$

$$AST_{t8} = m_9 - m_8 \quad = \quad \textit{Time to complete the eighth step} \quad \longrightarrow \quad (f_{23})$$

$$\sigma_{step} = \left(\frac{1}{8-1} \sum_{i=1}^{8} \left(AST_{ti} - \overline{AST_t} \right)^2 \right)^{\frac{1}{2}} \quad \longrightarrow \quad (f_{24})$$

$$\hat{\sigma}_{step} = \frac{\sigma_{step}}{AST_{Duration}} \quad \longrightarrow \quad (f_{25})$$

where

$$\overline{AST_t} = \frac{1}{8} \sum_{i=1}^{8} AST_{ti}$$

$\{f_{24}, f_{25}\}$ are the standard deviation of the individual step times, $\{AST_{t1}, AST_{t2}, ..., AST_{t8}\}$, and the standard deviation normalised as a fraction of the total duration of the task, $AST_{Duration}$.

5.3.2 Dissimilarity Metric

A measure of similarity was used to compare various cycles of the AST. The measure computes the mean signal morphology template for the compared cycles. That is, the average signal shape across the cycles. The metric uses the mean template to evaluate the average deviation away from the mean template as a fraction of the standard deviation of the mean signal template.

5.3.2.1 Preprocessing

The dissimilarity metric is evaluated using the low-pass filtered SVM of the AST (see Section 5.2.2). Figure 5.9 shows a block diagram of the processing. The SVM is low-pass filtered using a 10^{th} order Butterworth filter with a cut-off frequency of 5.0 Hz (a conservative estimate of the bandwidth of SVM signal given average time taken to complete the task, see section 6.1).

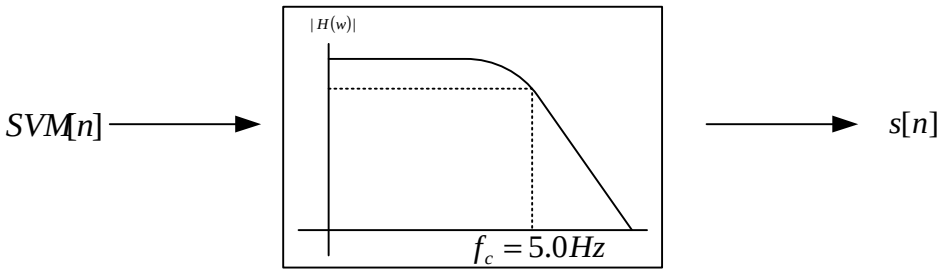


Figure 5.9 - Preprocessing of AST acceleration data

The segments of AST to be compared are extracted from the filtered output, $s[n]$. Figure 5.10 shows a representative sample of $s[n]$ for the AST example of Figure 5.8.

Before the chosen segments are compared, they are linearly warped in time via linear interpolation and resampling, so that each segment has 100 sample points. As an example, consider the comparison of the leading-foot steps $\{S_1, S_3, S_5, S_7\}$. Figure 5.11 shows the time warped segments $\{S_1, S_3, S_5, S_7\}$ for the data shown in Figure 5.10.

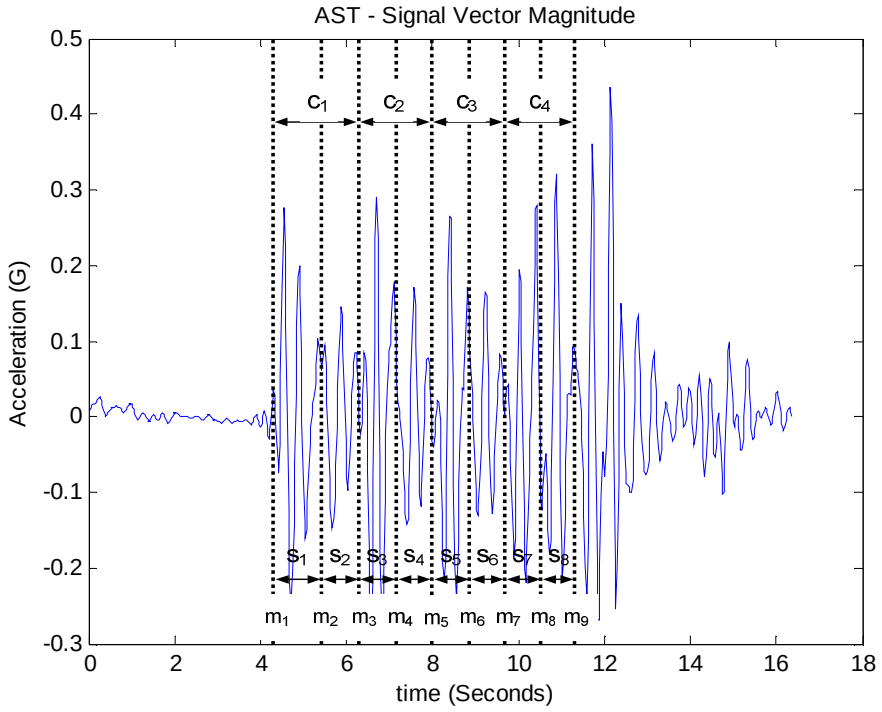


Figure 5.10 - The low-pass filtered signal vector magnitude, s[n], for the data shown in Figure 5.8.

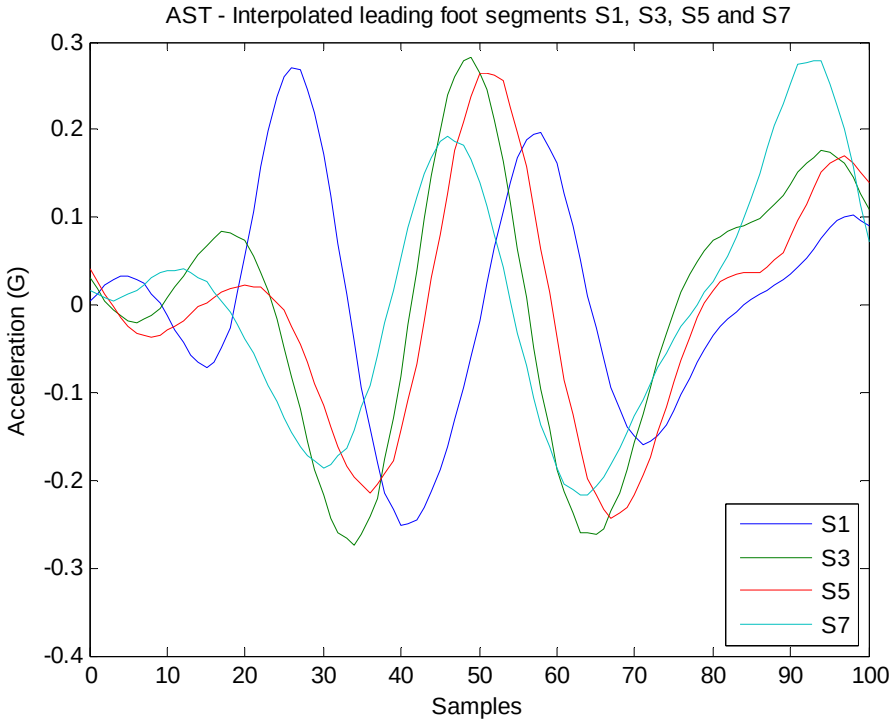


Figure 5.11 - Time warped segments of s[n] for the data shown in Figure 5.10.

5.3.2.2 Calculation of the dissimilarity metric

Consider the general case, for the comparison of *N*, time warped segments $\{\hat{S}_1, \hat{S}_2, ..., \hat{S}_N\}$ each 100 samples in length. The mean signal template for the warped segments, $\{\hat{S}_1, \hat{S}_2, ..., \hat{S}_N\}$, which represents the average signal morphology of the *N* segments, is calculated as:

$$template[n] = \frac{1}{N}\sum_{j=1}^{N} \hat{S}_j[n]$$

for $n = 1,...,100$. That is, the average of all segments. Figure 5.12 shows an example of the mean signal template for the leading-foot steps shown in Figure 5.11.

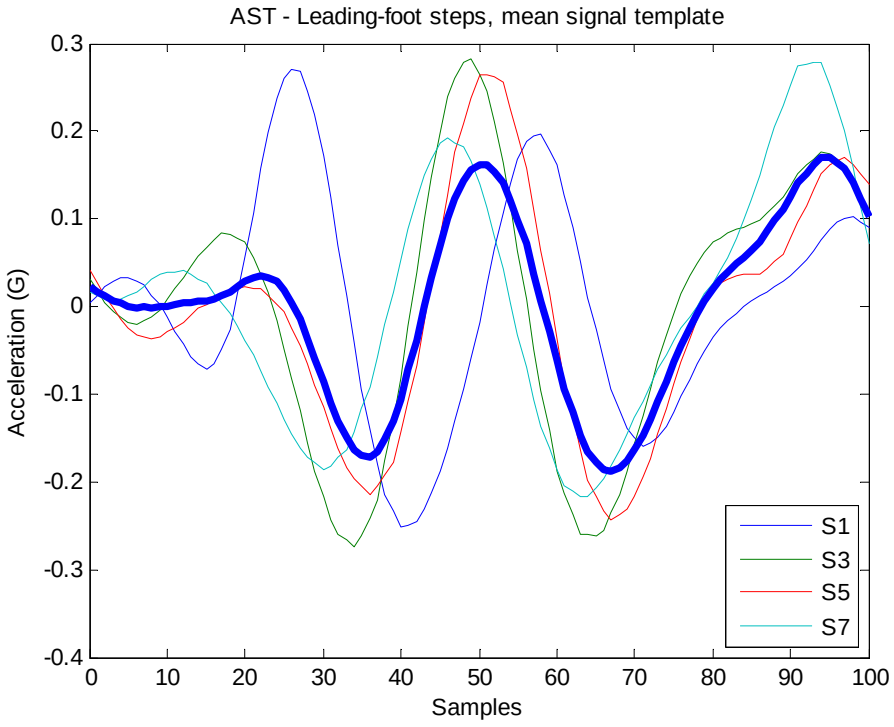


Figure 5.12 - Mean signal template (in bold) for the leading-foot steps shown in Figure 5.11.

The standard deviation of the mean signal template is thus:

$$\sigma_{template} = \left(\frac{1}{100-1} \sum_{i=1}^{100} \left(template[i] - \overline{template} \right)^2 \right)^{\frac{1}{2}}$$

where,

$$\overline{template} = \frac{1}{100} \sum_{i=1}^{100} template[i]$$

This relates to the natural amount of deviation in the compared segments. Next, we evaluate the average deviation of the segments from the mean signal template. This is calculated as the mean of the standard deviations of the segments, $\{\hat{S}_1, \hat{S}_2, ..., \hat{S}_N\}$, at each of the 100 sample points, from the mean signal template as follows:

$$\overline{\sigma_S} = \frac{1}{100} \sum_{i=1}^{100} \sigma_S[i]$$

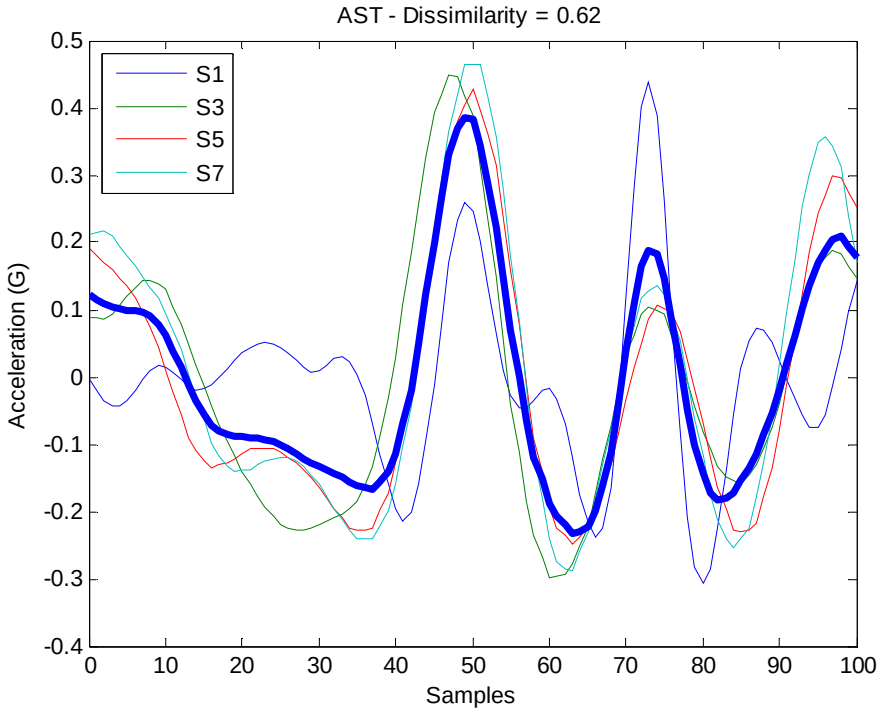
where,

$$\sigma_S[n] = \left(\frac{1}{N-1} \sum_{j=1}^{N} \left(\hat{S}_j[n] - template[n] \right)^2 \right)^{\frac{1}{2}}$$

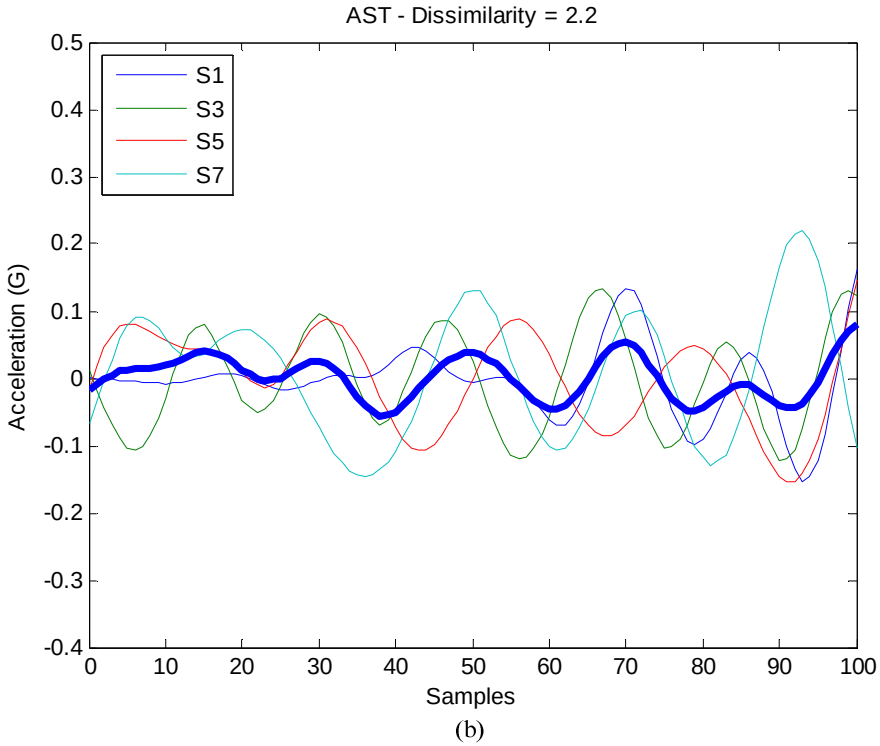
for $n = 1,...,100$. Finally, this average deviation from the mean signal template, $\overline{\sigma_S}$, is normalised as a fraction of the overall deviation in the mean signal template as follows:

$$dissimilarity = \frac{\overline{\sigma_S}}{\sigma_{template}} \qquad \longrightarrow \quad (1)$$

This is the dissimilarity metric. Figure 5.13 shows the leading-foot step cycles for two subjects, one whose leading-foot cycles appear quite similar (dissimilarity = 0.62) and the other, for a subject whose leading-foot cycles appear to differ significantly from one step to another, as indicated by the greater dissimilarity score (dissimilarity = 2.2).



(a)



(b)

Figure 5.13 - (a) Dissimilarity metric calculated for the AST leading-foot segments which are similar (b) Dissimilarity metric calculated for the AST leading-foot segments which are dissimilar.

4.3.2.2 Dissimilarity features

Using Equation (1), the following dissimilarity features are evaluated for the AST: $Dissimilarity_{Leading}$ (f_{26}), which compares segments $\{S_1, S_3, S_5, S_7\}$ of the AST as shown in Figure 5.14; $Dissimilarity_{Trailing}$ (f_{27}) which compares segments $\{S_2, S_4, S_6, S_8\}$ of the AST as shown in Figure 5.15; $Dissimilarity_{Cycles}$(f_{28}) which compares cycles $\{C_1, C_2, C_3, C_4\}$ of the AST as shown in Figure 5.16.

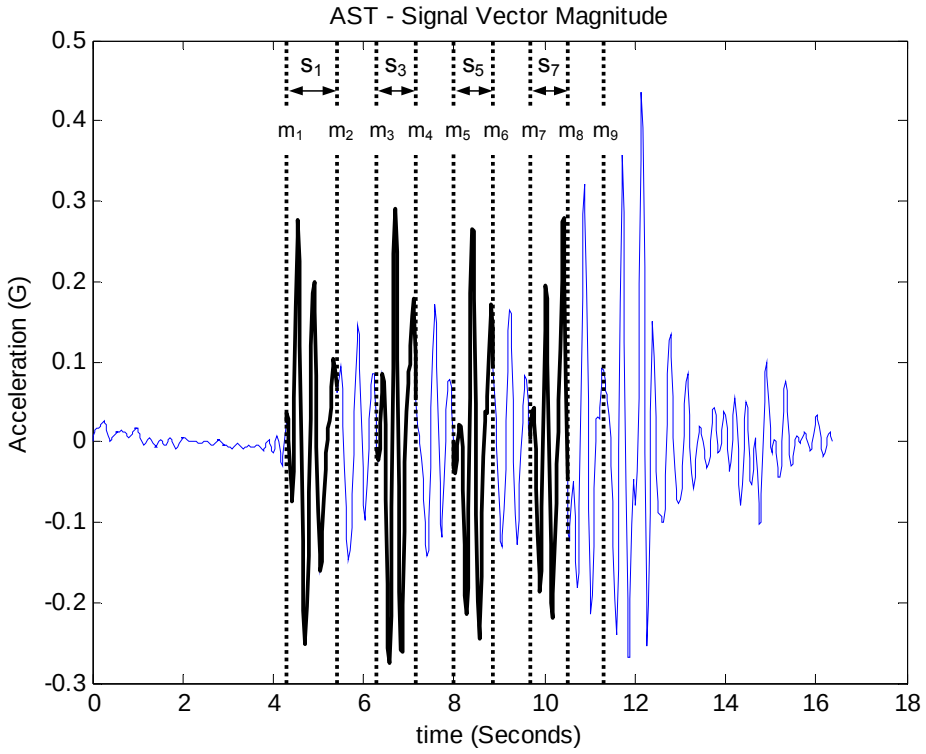


Figure 5.14 - A representative sample of the AST in which the leading-foot steps, {S1, S3, S5, S7}, are highlighted. f26, is the dissimilarity of {S1, S3, S5, S7}.

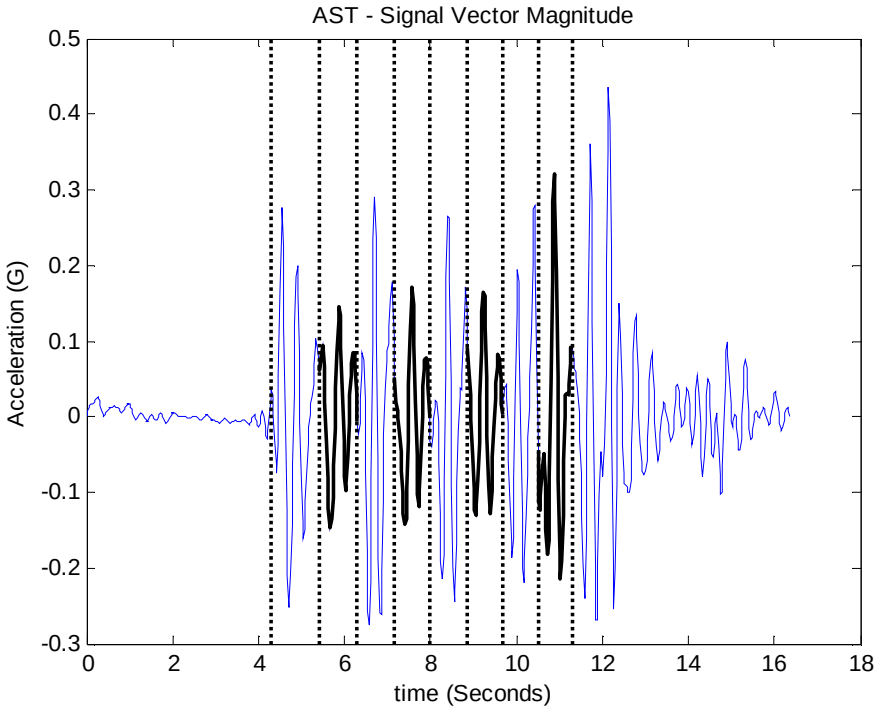


Figure 5.15 - A representative sample of the AST in which the trailing-foot steps, {S2, S4, S6, S8}, are highlighted. f_{27}, is the dissimilarity of {S2, S4, S6, S8}.

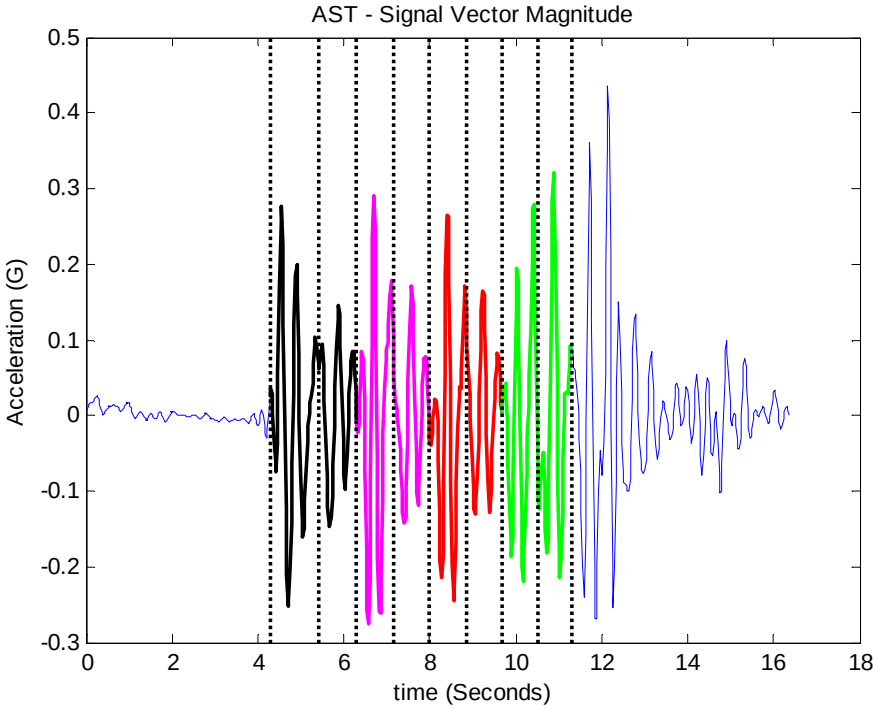


Figure 5.16 - A representative sample of the AST in which the AST cycles, {C1, C2, C3, C4}, are highlighted. f_{28}, is the dissimilarity of {C1, C2, C3, C4}.

5.3.3 Energy features

Like the TUGT, energy parameters for the AST are extracted from the BA components of the AST, using the SVM and SMA (see Section 5.2.2). The RMS for the AST is calculated as:

$$AST_{SVM\,RMS} = \sqrt{\frac{1}{m_9 - m_1}\sum_{i=m_1}^{m_9} SVM[i]^2} \quad \longrightarrow \quad (f_{29})$$

The SMA is evaluated for each of the AST step segments, $\{S_1, S_2, ..., S_8\}$, where:

$$AST\ SMA_{S_i} = \sum_{j=m_i}^{m_{i+1}} SM[j] \quad for\ i = 1,\ldots,8$$

where,

$$SM[n] = \left(|x_{BA}[n]| + |y_{BA}[n]| + |z_{BA}[n]|\right)$$

$AST\ SMA_{S_i}$ is the estimated energy expenditure for the i^{th} AST step. The estimated total energy expenditure for the AST is thus:

$$AST\ SMA = \sum_{i=1}^{8} AST\ SMA_{S_i} \quad \longrightarrow \quad (f_{30}).$$

$\{AST\ SMA_{S_1}, AST\ SMA_{S_2}, ..., AST\ SMA_{S_8}\}$ constitute features $\{f_{30}, f_{31}, ..., f_{37}\}$. Figure 5.17 shows a representative example of the estimated total energy expenditure for the AST, which is represented as the area under the SM curve between the first and last observer placed markers. Figure 5.18 illustrates the estimated energy expenditures for each of the AST steps. The estimates for the leading steps, $\{S_1, S_3, S_5, S_7\}$, are shaded in green while the estimates for the trailing steps, $\{S_2, S_4, S_6, S_8\}$, are shaded in blue.

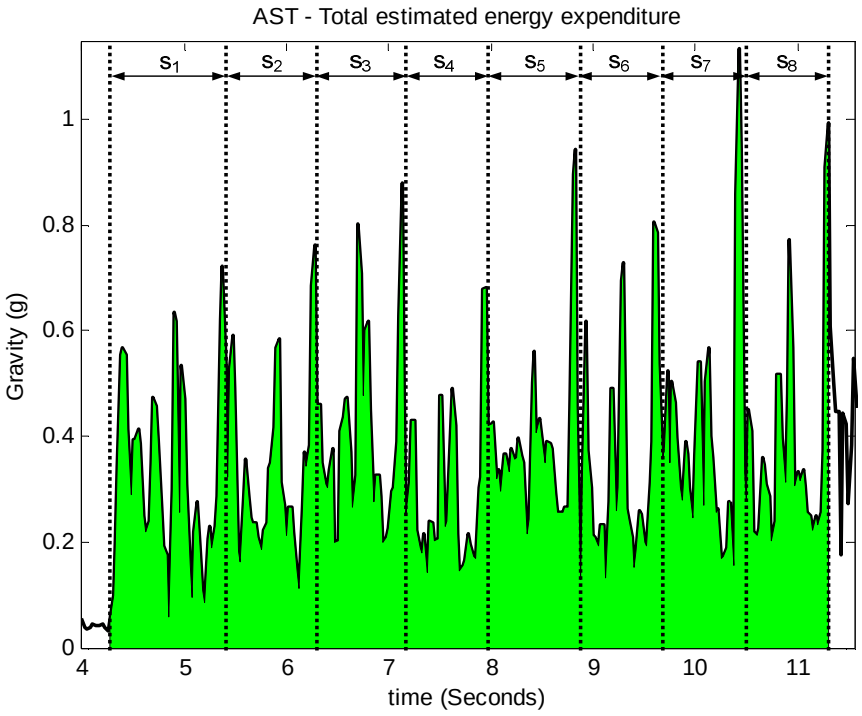


Figure 5.17 - A representative sample of the SM for an AST. The total energy expenditure for the AST equals the area under the SM curve.

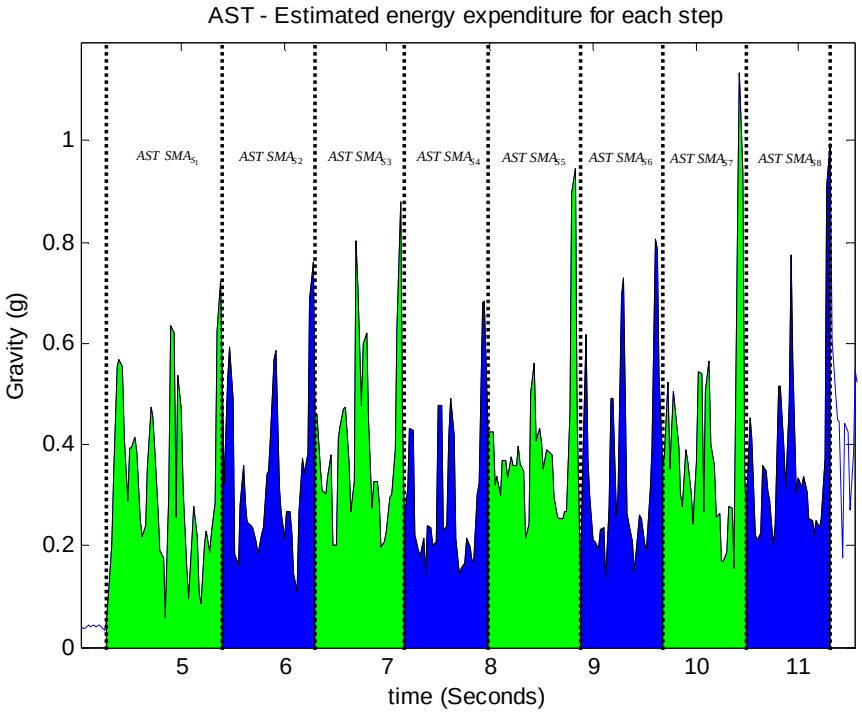


Figure 5.18 - A representative sample of the SM for an AST. The estimated energy expenditures for the leading-foot steps and trailing-foot steps are highlighted in green and blue respectively.

From the estimated energy expenditures for each AST step, the energy expenditures for each of the AST cycles, $\{C_1, C_2, C_3, C_4\}$, are calculated as:

$$AST\ SMA_{C1} = AST\ SMA_{S_1} + AST\ SMA_{S2}$$
$$AST\ SMA_{C2} = AST\ SMA_{S3} + AST\ SMA_{S4}$$
$$AST\ SMA_{C3} = AST\ SMA_{S5} + AST\ SMA_{S6}$$
$$AST\ SMA_{C4} = AST\ SMA_{S7} + AST\ SMA_{S8}$$

Figure 5.19 illustrates the AST cycle energy expenditures, with the SMA for each step pair highlighted.

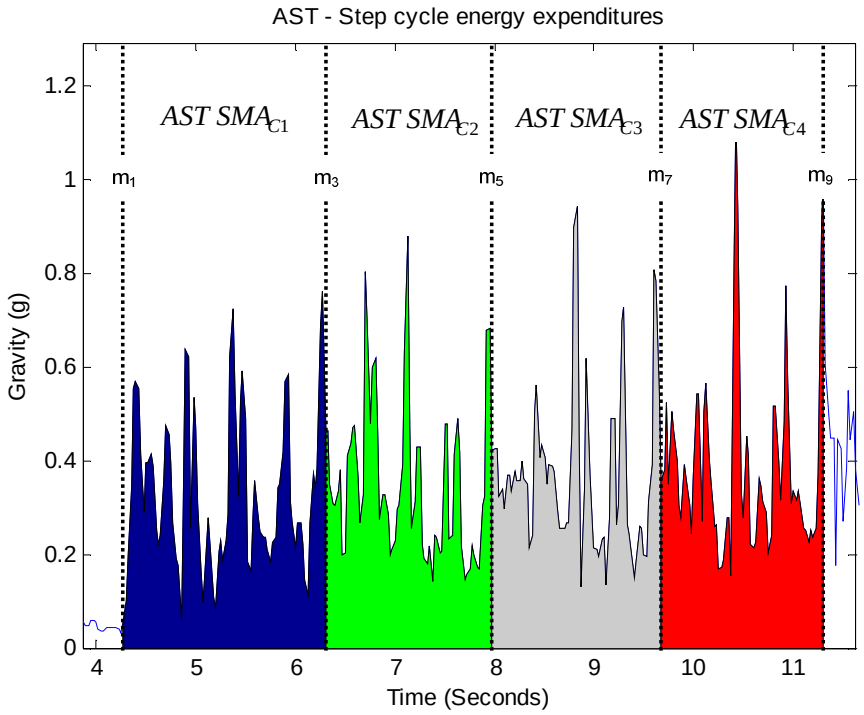


Figure 5.19 - A representative sample of the SM for an AST. The estimated energy expenditures for the AST cycles, {C1, C2, C3, C4}, are highlighted in blue, green, grey and red respectively.

From the energy expenditures per cycle, the following parameters are defined:

$$AST\ SMA_{MIN} = \min(AST\ SMA_{C1}, AST\ SMA_{C2}, AST\ SMA_{C3}, AST\ SMA_{C4}) \longrightarrow (f_{38})$$

$$AST\ SMA_{MAX} = \max(AST\ SMA_{C1}, AST\ SMA_{C2}, AST\ SMA_{C3}, AST\ SMA_{C4}) \longrightarrow (f_{39})$$

$$AST\ SMA_{Range} = AST\ SMA_{MAX} - AST\ SMA_{MIN} \longrightarrow (f_{40})$$

$$AST\ SMA_{Ratio} = \frac{AST\ SMA_{MAX}}{AST\ SMA_{MIN}} \longrightarrow (f_{41})$$

$$AST\ SMA_{\sigma^2} = \frac{1}{4-1}\sum_{i=1}^{4}\left(AST\ SMA_{Ci} - \overline{AST\ SMA_{C}}\right)^2 \longrightarrow (f_{42})$$

where,

$$\overline{AST\ SMA_{C}} = \frac{1}{4}\sum_{i=1}^{4} AST\ SMA_{Ci}$$

$AST\ SMA_{MIN}$ and $AST\ SMA_{MAX}$ are the minimum and maximum estimated energy expenditures for the AST step cycles $\{C_1, C_2, C_3, C_4\}$. $AST\ SMA_{RANGE}$ is the difference between the energy expenditures of the most energetic cycle and least energetic cycle, as measured by the SMA. Similarly, $AST\ SMA_{RATIO}$ is the ratio between the most energetic and least energetic AST cycles. $AST\ SMA_{\sigma^2}$ is the variation in the estimated energy expenditures for each of the AST cycles.

From the energy expenditures per step, the following parameters are defined:

$$AST\ SMA_{leading} = \sum_{i} AST\ SMA_{S_i} \quad for\ i = \{1,3,5,7\} \longrightarrow (f_{43})$$

$$AST\ SMA_{trailing} = \sum_{i} AST\ SMA_{S_i} \quad for\ i = \{2,4,6,8\} \longrightarrow (f_{44})$$

$$AST\ SMA_{stepRatio} = \frac{AST\ SMA_{leading}}{AST\ SMA_{trailing}} \longrightarrow (f_{45})$$

$$AST\ SMA_{leading\sigma^2} = \frac{1}{4}\sum_i \left(AST\ SMA_{S_i} - \overline{SMA_{leading}}\right)^2 \quad for\ i = \{1,3,5,7\} \longrightarrow (f_{46})$$

$$AST\ SMA_{trailing\sigma^2} = \frac{1}{4}\sum_i \left(AST\ SMA_{S_i} - \overline{SMA_{trailing}}\right)^2 \quad for\ i = \{2,4,6,8\} \longrightarrow (f_{47})$$

Where,

$$\overline{SMA_{leading}} = \frac{1}{4}\sum_i SMA_{S_i} \quad for\ i = \{1,3,5,7\},$$

$$\overline{SMA_{trailing}} = \frac{1}{4}\sum_i SMA_{S_i} \quad for\ i = \{2,4,6,8\}$$

$AST\ SMA_{leading}$ and $AST\ SMA_{trailing}$ are the estimates for the expended energy for the leading-foot and trailing-foot steps respectively. Figure 5.20 illustrates the evaluation of the energy expended during the leading-foot steps, which, is equal to the sum of the area under the SM curve during the leading-foot steps as indicated by the shaded regions.

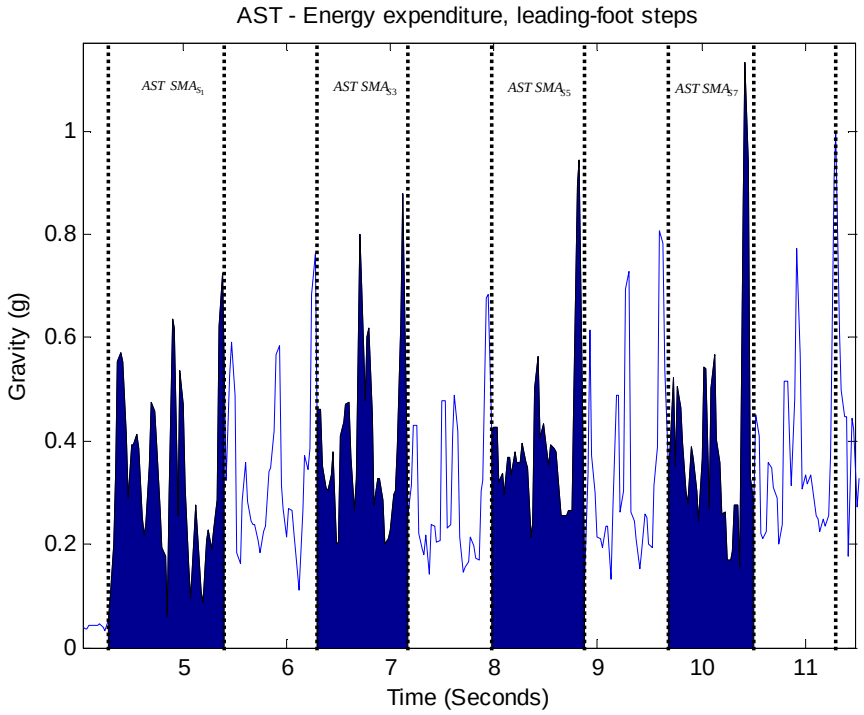


Figure 5.20 - $AST\ SMA_{leading}$ equals the sum of the area under the SM curve during AST steps S1, S3, S5 and S7 and is highlighted in blue.

$AST\ SMA_{stepRatio}$ is the ratio between the amount of energy expended during the leading-foot steps and the amount of energy expended during the trailing-foot steps. Finally, $AST\ SMA_{leading\sigma^2}$ and $AST\ SMA_{trailing\sigma^2}$ are the variation in the amount of energy expended during the leading-foot steps, $\{S_1, S_3, S_5, S_7\}$, and trailing-foot steps, $\{S_2, S_4, S_6, S_8\}$, respectively.

5.4 The Sit-to-Stand with five repetitions

The sit-to-stand, with five repetitions, is performed by doing five sit-to-stand (STS) transfers, with arms folded, as quickly as possible. Figure 5.21 shows a representative example of the acceleration data collected during an STS5. Six observer placed markers, $\{m_1, m_2, ..., m_6\}$, mark the start time for the task, as well as the end time for each of the STS transfers. Thus, the segment of data from m_1 to m_2 is the data for the first STS transfer, C_1, as shown in Figure 5.21. Similarly, from m_2 to m_3 is the second STS transfer, C_2, and so on.

5.4.1 Temporal parameters

The six STS5 markers, $\{m_1, m_2, ..., m_6\}$, are used to define a number of temporal parameters for the STS5.

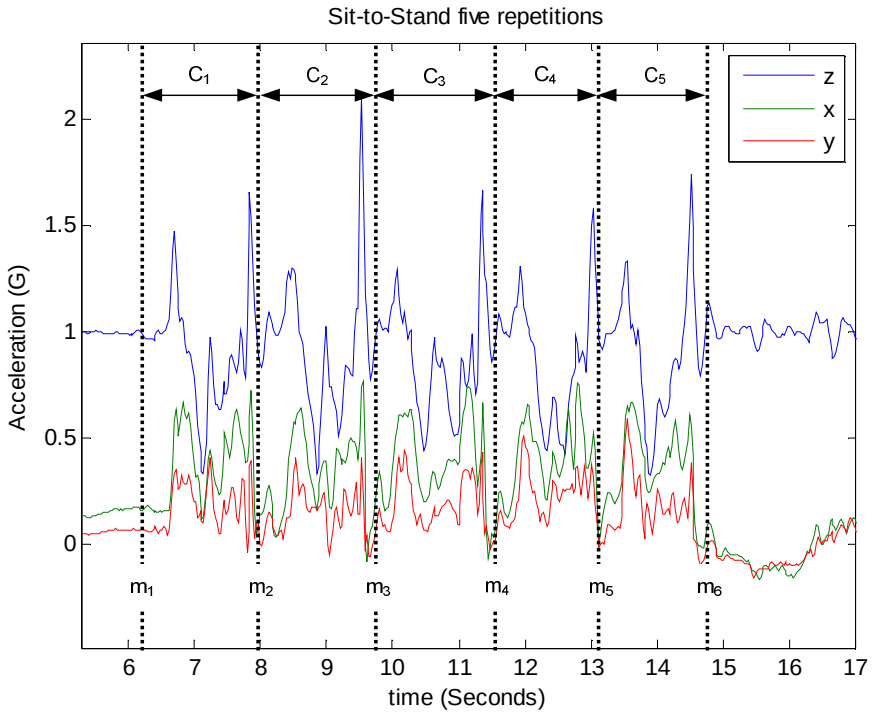


Figure 5.21 - Representative data for the STS5 showing the observer placed markers.

$$STS5_{Duration} = m_6 - m_1 \quad = \quad Time\ to\ complete\ the\ STS5 \longrightarrow (f_{49})$$

$$STS5_{t_1} = m_2 - m_1 \quad = \quad Time\ to\ complete\ the\ first\ STS\ transfer \longrightarrow (f_{50})$$

$$STS5_{t_2} = m_3 - m_2 \quad = \quad Time\ to\ complete\ the\ second\ STS\ transfer \longrightarrow (f_{51})$$

$$STS5_{t_3} = m_4 - m_3 \quad = \quad Time\ to\ complete\ the\ third\ STS\ transfer \longrightarrow (f_{52})$$

$$STS5_{t_4} = m_5 - m_4 \quad = \quad Time\ to\ complete\ the\ fourth\ STS\ transfer \longrightarrow (f_{53})$$

$$STS5_{t_5} = m_6 - m_5 \quad = \quad Time\ to\ complete\ the\ fifth\ STS\ transfer \longrightarrow (f_{54})$$

Using the individual STS transfer times, $\{STS5_{t_1}, STS5_{t2}, ..., STS5_{t_5}\}$, the standard deviation of the STS transfer times and normalised standard deviation of STS transfer times are evaluated as:

$$\sigma_{STS} = \left(\frac{1}{5-1} \sum_{i=1}^{8} \left(STS5_{ti} - \overline{STS5_t} \right)^2 \right)^{\frac{1}{2}} \longrightarrow (f_{55})$$

$$\hat{\sigma}_{STS} = \frac{\sigma_{STS}}{STS5_{Duration}} \longrightarrow (f_{56})$$

5.4.2 Dissimilarity features

Like the AST, the STS5 is quasi-periodic given the performance of repeated a movement. As such, the dissimilarity metric is evaluated across all STS transfers (see Section 5.3.2). Also like the AST, the dissimilarity metric is evaluated using the low-pass filtered SVM signal (see Section 5.3.2.1). The dissimilarity metric is the 57th feature (f_{57}). Figure 5.22 shows the signal for an STS5 and highlights the individual STS transfers, $\{C_1,C_2,\ldots,C_5\}$. Figure 5.23 shows the linearly interpolated STS5 cycles shown in Figure 5.22, overlaid with mean signal template, from which the dissimilarity is evaluated.

5.4.3 Energy features

Like the TUGT and AST, energy parameters for the STS5 are extracted from the BA components of the STS5, using the SVM and SMA (see Section 5.2.2). The RMS force for the STS5 is calculated as:

$$STS5_{SVM\,RMS} = \sqrt{\frac{1}{m_6 - m_1} \sum_{i=m_1}^{m_6} SVM[i]^2} \longrightarrow (f_{58})$$

The SMA is evaluated for each STS transfer, $\{C_1, C_2, ..., C_5\}$, where:

$$STS5\,SMA_{C_i} = \sum_{j=m_i}^{m_{i+1}} SM[j] \quad for\ i = 1,\ldots,5$$

where,

$$SM[n] = \left(|x_{BA}[n]| + |y_{BA}[n]| + |z_{BA}[n]|\right)$$

$STS5\,SMA_{C_i}$ is the estimated energy expenditure for the i^{th} STS transfer. The estimated total energy expenditure for the STS5 is thus:

$$STS5\,SMA = \sum_{i=1}^{5} STS\ SMA_{C_i} \quad \longrightarrow \quad (f_{59})$$

$\{STS5\,SMA_{C_1}, STS5\,SMA_{C_2}, \ldots, STS5\,SMA_{C_5}\}$ are features $\{f_{60}, f_{61}, \ldots, f_{64}\}$ respectively.

Figure 5.24 shows a representative example of the estimated total energy expenditure for the STS5, which is represented as the area under the SM curve between the first and last observer placed markers. Figure 5.25 illustrates the estimated energy expenditures for each of the STS transfers $\{C_1, C_2, \ldots, C_5\}$.

From the energy expenditures per cycle, the following parameters are defined:

$$STS5\ SMA_{MIN} = \min(STS5\ SMA_{C1}, STS5\ SMA_{C2}, ..., STS5\ SMA_{C5}) \longrightarrow (f_{65})$$

$$STS5\ SMA_{MAX} = \max(STS5\ SMA_{C1}, STS5\ SMA_{C2}, ..., STS5\ SMA_{C5}) \longrightarrow (f_{66})$$

$$STS5\ SMA_{Range} = STS5\ SMA_{MAX} - STS5\ SMA_{MIN} \longrightarrow (f_{67})$$

$$STS5\ SMA_{Ratio} = \frac{STS5\ SMA_{MAX}}{STS5\ SMA_{MIN}} \longrightarrow (f_{68})$$

$$STS5\ SMA_{\sigma^2} = \frac{1}{5-1}\sum_{i=1}^{5}\left(STS5\ SMA_{Ci} - \overline{STS5\ SMA_{C}}\right)^2 \longrightarrow (f_{69})$$

where,

$$\overline{STS5\ SMA_{C}} = \frac{1}{5}\sum_{i=1}^{5} STS5\ SMA_{Ci}$$

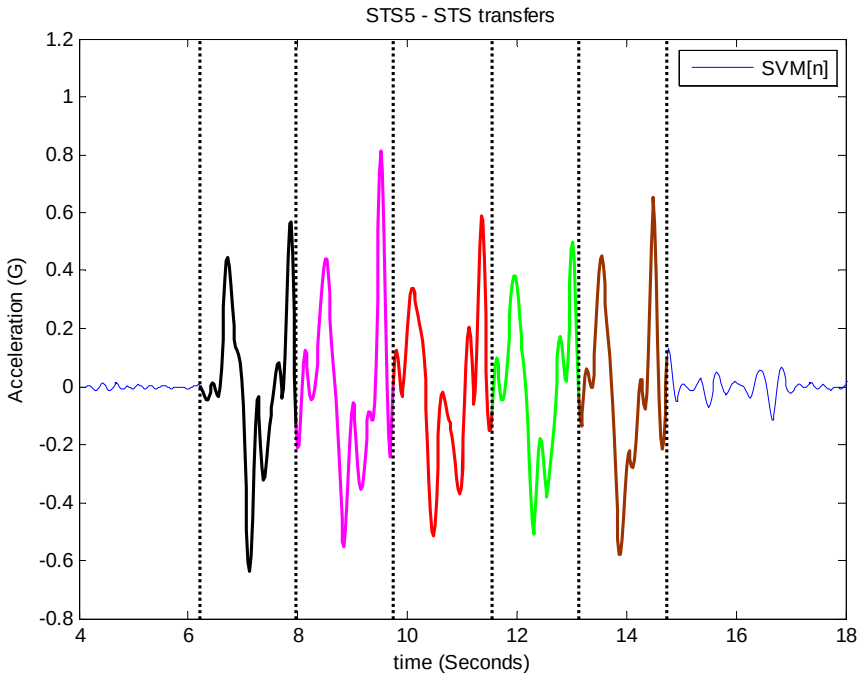


Figure 5.22 - Low-pass filtered SVM used to evaluate the dissimilarity in the STS5 cycles. Each of the compared cycles is highlighted in a unique colour.

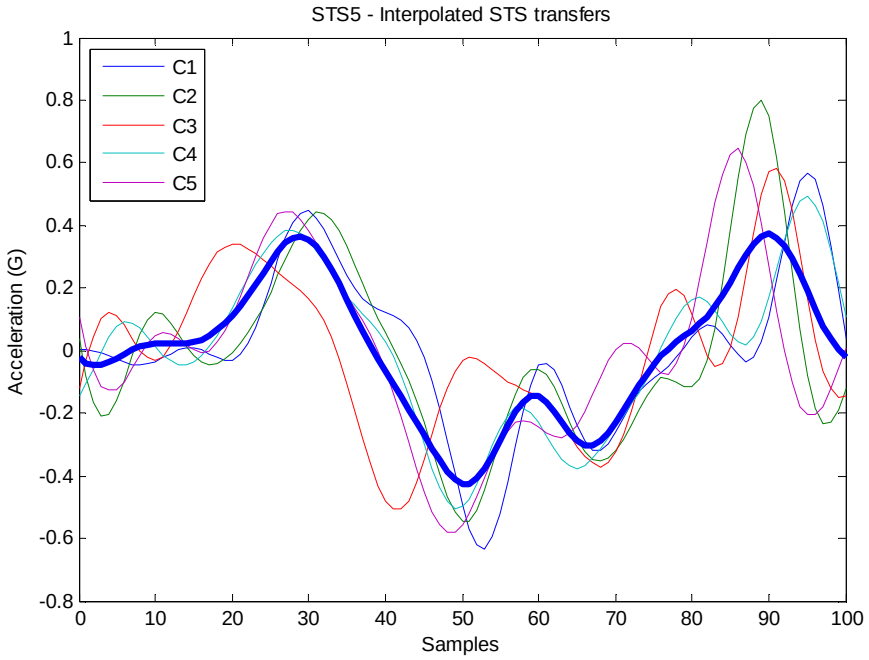


Figure 5.23 - Linearly interpolated STS5 cycles, C1,…,C5, shown in Figure 5.22. The mean signal template is overlaid onto the cycles and is shown in bold.

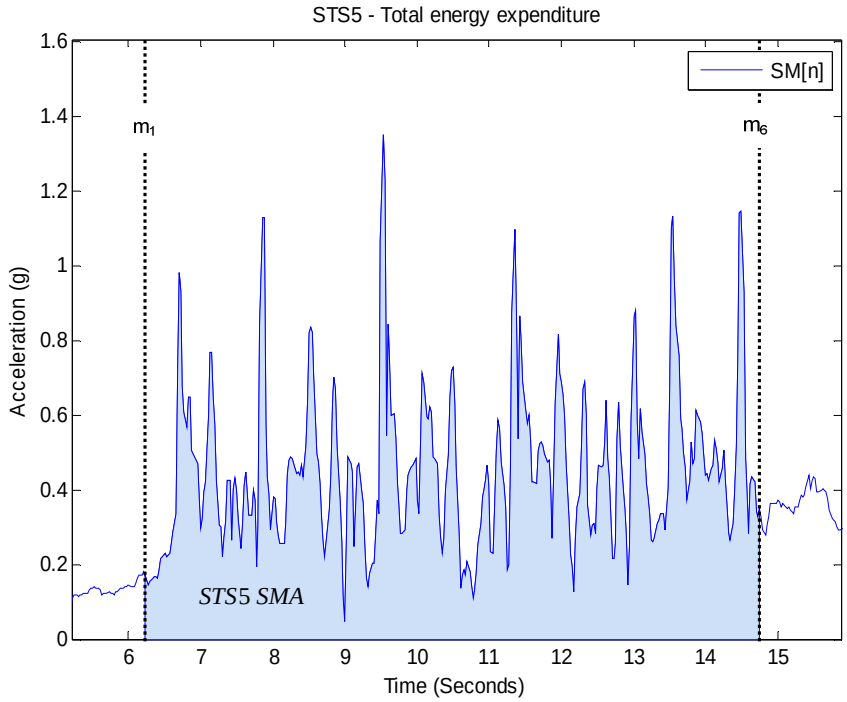


Figure 5.24 - *STS5 SMA* equals the area under the SM curve for the duration of the STS5 task. That is the area under the SM curve between m_1 and m_6.

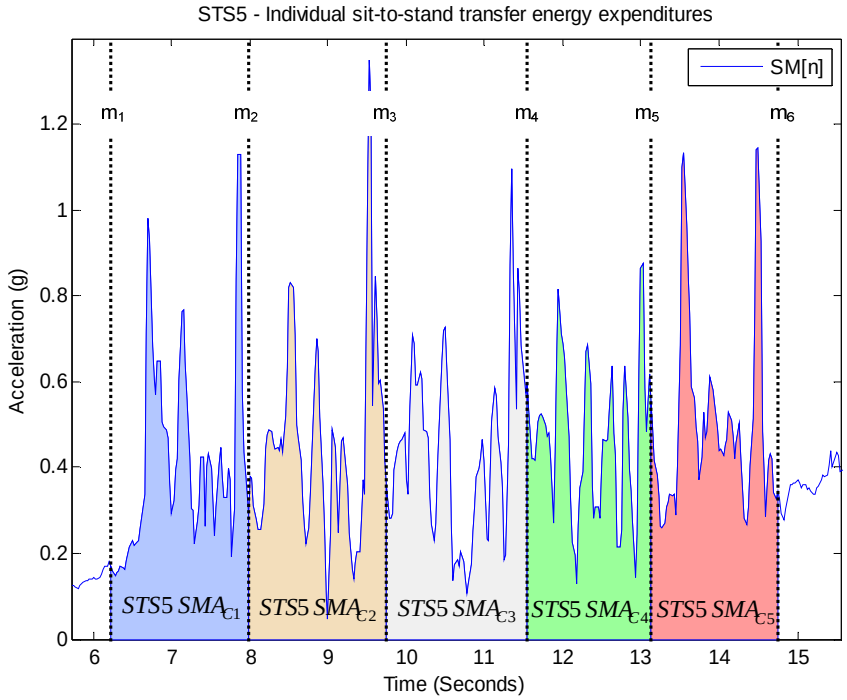


Figure 5.25 - The estimated energy expenditures, *STS5 SMA_{Ci}*, for each of the STS5 STS transfers. The estimated energy expended in the i^{th} cycle of the STS5 equals, the area under the SM curve between m_i and m_{i+1}.

5.5 Non-TA features

In addition to the features extracted from the TUGT, AST and STS5, a number of non-TA based features were added to the feature pool. The age and sex of the subject were considered useful features to add. Additionally, the reaction time standard score, RT z-score, was added to the feature pool. This feature was added to the pool as it is felt that a simple reaction time test can trivially be implemented by the TA. The TA has light emitting diodes and a buzzer that could be used to provide visual or audio stimuli that the user reacts to by pressing the pushbutton switch. Age, sex and RT z-score constitute features f_{70}, f_{71} and f_{72} respectively.

5.6 Summary

Sixty-nine TA-based features, plus three non-TA based features make up the feature pool used to model falls risk and functional ability in the elderly. Most of the features are simple temporal features, extracted using the observer placed markers, and energy based features, using a simple estimate of energy expenditure. Table 5.1 provides a summary of the entire feature pool.

TABLE 5.1
DISTRIBUTION OF FEATURES

Task	Feature	Feature Name	Description
TUGT	f_1	$TUGT_{Duration}$	Time to complete the TUGT
	f_2	$TUGT_{Stand}$	Time taken to stand up
	f_3	$TUGT_{3m}$	Time taken to walk to the 3 meter mark
	f_4	$TUGT_{Turn}$	Time taken to turn around
	f_5	$TUGT_{Chair}$	Time taken to walk back to the chair
	f_6	$TUGT_{Sit}$	Time taken to sit down
	f_7	f_{Step}	Estimated stepping frequency
	f_8	$TUGT_{SVM\ RMS}$	RMS SVM for the duration of the TUGT
	f_9	$TUGT_{SMA}$	Total estimated energy expenditure for the TUGT
	f_{10}	$TUGT_{SMA\ Stand}$	Estimated energy expenditure for the stand phase of the TUGT
	f_{11}	$TUGT_{SMA\ 3m}$	Estimated energy expenditure for walking from the chair to the 3 m mark
	f_{12}	$TUGT_{SMA\ Turn}$	Estimated energy expenditure while turning at the 3 m mark
	f_{13}	$TUGT_{SMA\ Chair}$	Estimated energy expenditure walking back to the chair
	f_{14}	$TUGT_{SMA\ Sit}$	Estimated energy expenditure during the sitting phase of the TUGT

Task	Feature	Feature Name	Description
	f_{15}	$AST_{Duration}$	Time taken to complete the AST
	f_{16}	AST_{t1}	Time taken to complete the first step
	f_{17}	AST_{t2}	Time taken to complete the second step
	f_{18}	AST_{t3}	Time taken to complete the third step
	f_{19}	AST_{t4}	Time taken to complete the fourth step
	f_{20}	AST_{t5}	Time taken to complete the fifth step
	f_{21}	AST_{t6}	Time taken to complete the sixth step
	f_{22}	AST_{t7}	Time taken to complete the seventh step
	f_{23}	AST_{t8}	Time taken to complete the eighth step
	f_{24}	σ_{step}	Standard deviation of the stepping times
	f_{25}	$\hat{\sigma}_{step}$	Normalised standard deviation of the stepping times
	f_{26}	$Dissim_{Leading}$	Dissimilarity of leading-foot steps for the AST
	f_{27}	$Dissim_{Trailing}$	Dissimilarity of trailing-foot steps for the AST
AST	f_{28}	$Dissim_{Cycles}$	Dissimilarity of the AST cycles
	f_{29}	$AST_{SVM\ RMS}$	RMS SVM for the duration of the AST
	f_{30}	AST_{SMA}	Total estimated energy expenditure for the AST
	f_{31}	AST_{S1}	Estimated energy expenditure for the first step
	f_{32}	AST_{S2}	Estimated energy expenditure for the second step
	f_{33}	AST_{S3}	Estimated energy expenditure for the third step
	f_{34}	AST_{S4}	Estimated energy expenditure for the fourth step
	f_{35}	AST_{S5}	Estimated energy expenditure for the fifth step
	f_{36}	AST_{S6}	Estimated energy expenditure for the sixth step
	f_{37}	AST_{S7}	Estimated energy expenditure for the seventh step
	f_{38}	AST_{S8}	Estimated energy expenditure for the eighth step
	f_{39}	$ASTSMA_{MIN}$	Least energetic AST cycle
	f_{40}	$ASTSMA_{MAX}$	Most energetic AST cycle
	f_{41}	$ASTSMA_{Range}$	Difference in energy expenditure between the most energetic and least energetic AST cycles

Task	Feature	Feature Name	Description
AST	f_{42}	$ASTSMA_{Ratio}$	Ratio between the most energetic and least energetic AST cycles
	f_{43}	$ASTSMA_{\sigma}^{2}$	Variation in energy expenditure for the AST cycles
	f_{44}	$ASTSMA_{Leading}$	Total estimated energy expenditure for leading-foot steps
	f_{45}	$ASTSMA_{Trailing}$	Total estimated energy expenditure for trailing-foot steps
	f_{46}	$ASTSMA_{StepRatio}$	Ratio in total energy expended during leading and trailing-foot steps
	f_{47}	$ASTSMA_{leading\sigma}^{2}$	Variation in energy expenditure for the leading-foot steps
	f_{48}	$ASTSMA_{trailing\sigma}^{2}$	Variation in energy expenditure for the trailing-foot steps
STS5	f_{49}	$STS5_{Duration}$	Time taken to complete the STS5
	f_{50}	$STS5_{t1}$	Time taken to complete the first STS transfer
	f_{51}	$STS5_{t2}$	Time taken to complete the second STS transfer
	f_{52}	$STS5_{t3}$	Time taken to complete the third STS transfer
	f_{53}	$STS5_{t4}$	Time taken to complete the fourth STS transfer
	f_{54}	$STS5_{t5}$	Time taken to complete the fifth STS transfer
	f_{55}	σ_{STS}	Standard deviation of the STS transfer times
	f_{56}	$\hat{\sigma}_{STS}$	Normalised standard deviation of the STS transfer times
	f_{57}	$Dissim_{STS}$	Dissimilarity of the STS transfers
	f_{58}	$STS5_{SVM\ RMS}$	RMS SVM for the duration of the STS5
	f_{59}	$STS5_{SMA}$	Total estimated energy expenditure for the STS5
	f_{60}	$STS5_{S1}$	Estimated energy expenditure for the first STS transfer
	f_{61}	$STS5_{S2}$	Estimated energy expenditure for the second STS transfer
	f_{62}	$STS5_{S3}$	Estimated energy expenditure for the third STS transfer
	f_{63}	$STS5_{S4}$	Estimated energy expenditure for the fourth STS transfer
	f_{64}	$STS5_{S5}$	Estimated energy expenditure for the fifth STS transfer
	f_{65}	$STS5SMA_{MIN}$	Least energetic STS5 cycle

Task	Feature	Feature Name	Description
STS5	f_{66}	$STS5SMA_{MAX}$	Most energetic STS5 cycle
	f_{67}	$STS5SMA_{Range}$	Difference in energy expenditure between the most energetic and least energetic STS5 cycles
	f_{68}	$STS5SMA_{Ratio}$	Ratio between the most energetic and least energetic STS5 cycles
	f_{69}	$STS5SMA_{\sigma}^{2}$	Variation in energy expenditure for the STS5 cycles
---	f_{70}	Age	
	f_{71}	Sex	
	f_{72}	RT *z-score*	Standardised reaction time score

5.7 Chapter conclusion

This chapter describes a candidate set of 72 features including 69 features extracted from the TUGT, AST and STS5 DR movement tasks, and 3 non-TA-based features obtained from the PPA are evaluated. Temporal parameters and energy parameters are extracted from the TUGT, AST and STS5. A dissimilarity metric was defined and calculated over various phases of the quasi-periodic AST and STS5 DR movement tasks. Three non-TA-based features, Age, Sex and RT *z-score*, were considered candidate features. Using the light-emitting diodes or buzzer on the TA, a simple reaction time test can easily be implemented. The following chapter presents the performance results for models of falls risk and the PPA assessment tasks, using the 72 candidate features described in this chapter.

6 Results

6.1 Introduction

A cohort of (N = 68) of subjects (21 men and 47 women) aged 72-91 years (mean 80.0, standard deviation (SD) = 4.42 years), randomly selected from attendees of a falls risk clinic at the Prince of Wales Medical Research Institute (Sydney, Australia) were assessed for falls risk using the PPA. The observed PPA falls risk scores ranged from very low (-1.19) to marked (4.41). The mean PPA falls risk score for the cohort was found to be 0.520, representing a mild falls risk. With a SD of 0.958, the majority of the cohort had between a low to moderate risk of falling.

The 68 subjects were assessed using the TA, via a DR comprising of the TUGT, AST and STS5 mobility tasks. Administration times for each DR task in this study were: mean 10.1 s and SD 2.97 s, for the TUGT; mean 11.3 s and SD 3.16 s, for the AST; mean 12.8 s and SD 4.50 s, for the STS5.

72 features (69 TA features and 3 non-TA features), were extracted from the DR and PPA data (see Chapter 5). This chapter assesses the relationship between the extracted features and the PPA falls risk score and four of the PPA subtasks, namely, knee-extension strength, proprioception, body sway and the Melbourne Edge Test (MET).

Additionally, this chapter describes the performance of the derived, linear least-squares models in which sequential forward floating search algorithm (see Section 4.4.1.4) was

used in an attempt to find the optimal subsets of the 72 features, to model falls risk and four of the PPA subtasks, namely, knee-extension strength, proprioception, body sway and the Melbourne Edge Test.

6.2 Correlation statistics

Table 6.1 shows typical values for the 69 extracted TA features and 3 non-TA based features, expressed as mean and standard deviation for each feature. Table 6.1 also describes the relationship, of each of the 72 features, with the falls risk score and the standard scores for each of: knee-extension strength; proprioception; body sway; and the MET, obtained from the PPA. The relationship is expressed as Pearson's correlation coefficients (ρ) with the statistical significance (*P*-value) shown. Significance level was taken at P=0.05.

6.2.1 TUGT correlation statistics

From Table 6.1, it can be seen that a number of features extracted from the TUGT are significantly associated with the falls risk score, knee-extension strength score and body sway score. No associations were found between the TUGT features and the proprioception score and the Melbourne Edge Test score.

6.2.2 AST correlation statistics

From Table 6.1, it can be seen that, like the TUGT features, a number of features extracted from the AST are significantly associated with the falls risk score, knee-extension strength score and body sway score. No associations were found between the AST features and the proprioception score and the Melbourne Edge Test score.

6.2.3 STS5 correlation statistics

From Table 6.1, it can be seen that a number of features extracted from the STS5 are significantly associated with the falls risk score and body sway score, only. No associations were found between the STS5 features and the knee-extension strength score, proprioception score and the Melbourne Edge Test score.

6.2.4 Non-TA features correlation statistics

Age does not show any significant correlation with the observed PPA falls risk, knee-extension strength, proprioception, body sway or MET scores for the cohort of 68 elderly subjects. Sex (ρ=0.587, P<0.001) shows a significant (P<0.005) association with knee extension strength but not with falls risk, proprioception, body sway or the MET. The reaction time standard score, RT *z-score*, was found to have the strongest association, (ρ=-0.709, P<0.001), with falls risk and was the only feature, out of 72, to be

significantly associated with the MET (ρ=0.350, *P*=0.003). As expected, RT z-score does not significantly associate with knee-extension strength, proprioception and body sway.

TABLE 6.1
DISTRIBUTION OF FEATURES AND CORRELATION WITH THE PPA

Task	Feature	Feature Name	Mean	SD	Falls Risk		Knee-extension Strength		Proprioception		Body Sway		MET	
					P	*P*-value	P	*P*-value	ρ	*P*-value	ρ	*P*-value	ρ	*P*-value
TUGT	f_1	$TUGT_{Duration}$	10.1	2.97	**0.387**	0.001	-0.230	0.060	-0.159	0.194	**-0.373**	0.002	-0.079	0.523
	f_2	$TUGT_{Stand}$	1.43	0.454	**0.271**	0.026	-0.152	0.216	-0.168	0.171	-0.237	0.052	-0.080	0.519
	f_3	$TUGT_{3m}$	2.81	0.818	**0.339**	0.005	**-0.279**	0.021	-0.139	0.260	**-0.335**	0.005	-0.092	0.457
	f_4	$TUGT_{Turn}$	1.05	0.442	**0.244**	0.045	-0.227	0.062	-0.130	0.291	**-0.247**	0.042	-0.023	0.850
	f_5	$TUGT_{Chair}$	3.07	0.849	**0.412**	< 0.001	-0.161	0.190	-0.081	0.511	**-0.323**	0.007	-0.161	0.190
	f_6	$TUGT_{Sit}$	1.69	0.968	**0.301**	0.013	-0.152	0.215	-0.162	0.186	**-0.353**	0.003	0.025	0.838
	f_7	f_{Step}	1.90	0.179	-0.162	0.188	-0.102	0.407	-0.228	0.061	0.205	0.093	0.156	0.203
	f_8	$TUGT_{SVM\ RMS}$	0.110	0.037	-0.153	0.212	**0.425**	< 0.001	0.219	0.073	**0.246**	0.043	-0.112	0.362
	f_9	$TUGT_{SMA}$	187	34.9	0.188	0.125	-0.075	0.543	-0.089	0.472	-0.053	0.669	-0.105	0.394
	f_{10}	$TUGT_{SMA\ Stand}$	30.5	10.0	0.209	0.087	-0.121	0.327	-0.068	0.581	-0.164	0.181	-0.009	0.941
	f_{11}	$TUGT_{SMA\ 3m}$	49.3	10.3	0.019	0.875	-0.076	0.538	-0.030	0.807	0.086	0.485	-0.052	0.674
	f_{12}	$TUGT_{SMA\ Turn}$	16.1	5.06	0.008	0.949	0.100	0.419	0.063	0.612	0.073	0.557	-0.213	0.081
	f_{13}	$TUGT_{SMA\ Chair}$	53.2	14.3	0.087	0.483	0.063	0.612	-0.035	0.775	0.139	0.259	-0.207	0.090
	f_{14}	$TUGT_{SMA\ Sit}$	38.0	11.3	**0.265**	0.029	-0.181	0.140	-0.170	0.166	**-0.305**	0.011	0.090	0.465
AST	f_{15}	$AST_{Duration}$	11.3	3.16	**0.373**	0.002	**-0.301**	0.013	-0.101	0.410	**-0.411**	< 0.001	0.027	0.830
	f_{16}	AST_{t1}	1.81	0.418	**0.308**	0.011	**-0.275**	0.023	-0.101	0.412	**-0.342**	0.004	0.037	0.767
	f_{17}	AST_{t2}	1.39	0.491	**0.368**	0.002	**-0.310**	0.010	-0.111	0.369	**-0.466**	< 0.001	0.029	0.813
	f_{18}	AST_{t3}	1.37	0.436	**0.321**	0.008	**-0.315**	0.009	-0.115	0.352	**-0.353**	0.003	0.033	0.792

Task	Feature	Feature Name	Mean	SD	Falls Risk		Knee-extension Strength		Proprioception		Body Sway		MET	
					P	*P*-value	P	*P*-value	ρ	*P*-value	ρ	*P*-value	ρ	*P*-value
AST	f_{19}	AST_{t4}	1.37	0.441	**0.390**	0.001	**-0.277**	0.022	-0.128	0.297	**-0.434**	< 0.001	0.009	0.944
	f_{20}	AST_{t5}	1.32	0.399	**0.315**	0.009	**-0.311**	0.010	-0.110	0.373	**-0.329**	0.006	0.095	0.442
	f_{21}	AST_{t6}	1.33	0.414	**0.419**	0.000	**-0.270**	0.026	-0.125	0.312	**-0.444**	< 0.001	-0.007	0.952
	f_{22}	AST_{t7}	1.31	0.398	**0.297**	0.014	**-0.264**	0.029	-0.027	0.829	**-0.301**	0.013	0.032	0.795
	f_{23}	AST_{t8}	1.36	0.409	**0.346**	0.004	-0.207	0.091	-0.029	0.816	**-0.365**	0.002	-0.027	0.826
	f_{24}	σ_{step}	0.006	0.002	0.232	0.057	-0.071	0.566	-0.157	0.200	**-0.326**	0.007	0.023	0.852
	f_{25}	$\hat{\sigma}_{step}$	0.001	< 0.001	-0.039	0.752	0.195	0.111	-0.044	0.721	-0.015	0.903	-0.036	0.770
	f_{26}	$Dissim_{Leading}$	1.27	0.339	**0.341**	0.004	**-0.327**	0.006	-0.158	0.199	**-0.327**	0.006	-0.123	0.316
	f_{27}	$Dissim_{Trailing}$	1.12	0.481	**0.333**	0.005	**-0.426**	< 0.001	-0.231	0.058	**-0.361**	0.002	0.022	0.860
	f_{28}	$Dissim_{Cycles}$	1.30	0.387	0.205	0.094	**-0.306**	0.011	-0.140	0.255	**-0.290**	0.016	0.110	0.373
	f_{29}	$AST_{SVM\ RMS}$	0.098	0.047	**-0.241**	0.047	**0.340**	0.005	0.047	0.704	**0.257**	0.034	-0.062	0.615
	f_{30}	AST_{SMA}	140	38.0	0.166	0.175	0.061	0.623	-0.044	0.721	-0.018	0.885	-0.091	0.461
	f_{31}	AST_{S1}	19.000	6.710	-0.019	0.876	0.182	0.138	-0.082	0.507	0.133	0.279	-0.088	0.477
	f_{32}	AST_{S2}	17.200	5.580	0.133	0.280	0.109	0.376	-0.001	0.992	0.001	0.993	-0.081	0.509
	f_{33}	AST_{S3}	18.000	5.080	0.111	0.369	-0.059	0.632	-0.128	0.299	0.027	0.830	-0.011	0.927
	f_{34}	AST_{S4}	17.100	5.970	**0.268**	0.027	0.075	0.542	-0.049	0.692	-0.137	0.265	-0.138	0.262
	f_{35}	AST_{S5}	17.300	5.820	0.111	0.367	-0.084	0.498	-0.101	0.414	-0.049	0.692	-0.002	0.984
	f_{36}	AST_{S6}	16.700	5.210	0.235	0.054	0.058	0.640	-0.060	0.628	-0.054	0.664	-0.127	0.301
	f_{37}	AST_{S7}	18.100	5.420	0.103	0.405	0.002	0.984	0.067	0.588	-0.038	0.757	-0.020	0.872
	f_{38}	AST_{S8}	16.200	5.740	0.196	0.110	0.088	0.477	0.062	0.616	-0.022	0.859	-0.131	0.287

Task	Feature	Feature Name	Mean	SD	Falls Risk		Knee-extension Strength		Proprioception		Body Sway		MET	
					P	*P*-value	P	*P*-value	ρ	*P*-value	ρ	*P*-value	ρ	*P*-value
AST	f_{39}	$ASTSMA_{MIN}$	31.4	8.57	0.165	0.178	0.056	0.650	-0.006	0.964	-0.011	0.931	-0.105	0.392
	f_{40}	$ASTSMA_{MAX}$	38.8	10.8	0.119	0.335	0.098	0.427	-0.050	0.683	0.006	0.960	-0.050	0.685
	f_{41}	$ASTSMA_{Range}$	7.35	4.33	-0.030	0.809	0.134	0.276	-0.115	0.350	0.037	0.767	0.083	0.499
	f_{42}	$ASTSMA_{Ratio}$	1.24	0.131	-0.065	0.598	0.175	0.153	-0.077	0.534	0.017	0.889	0.073	0.556
	f_{43}	$ASTSMA_{\sigma}^{2}$	14.4	18.1	-0.076	0.539	0.056	0.648	-0.144	0.240	0.051	0.680	0.142	0.248
	f_{44}	$ASTSMA_{Leading}$	72.4	20.7	0.079	0.522	0.022	0.862	-0.069	0.578	0.026	0.834	-0.037	0.764
	f_{45}	$ASTSMA_{Trailing}$	67.3	21.4	0.219	0.073	0.087	0.480	-0.012	0.923	-0.057	0.645	-0.126	0.307
	f_{46}	$ASTSMA_{StepRatio}$	1.11	0.259	-0.140	0.255	-0.018	0.883	-0.090	0.464	0.103	0.405	0.061	0.619
	f_{47}	$ASTSMA_{leading\sigma}^{2}$	9.26	10.1	-0.077	0.532	**0.242**	0.047	-0.040	0.749	0.065	0.601	0.113	0.359
	f_{48}	$ASTSMA_{trailing\sigma}^{2}$	4.27	5.04	0.078	0.527	-0.206	0.093	-0.143	0.246	-0.130	0.291	0.147	0.232
STS5	f_{49}	$STS5_{Duration}$	12.8	4.50	**0.367**	0.002	-0.152	0.216	-0.091	0.460	**-0.425**	< 0.001	-0.022	0.859
	f_{50}	$STS5_{t1}$	2.59	1.22	**0.317**	0.008	-0.095	0.439	-0.100	0.417	**-0.376**	0.002	-0.045	0.716
	f_{51}	$STS5_{t2}$	2.57	0.923	**0.410**	0.001	-0.121	0.325	-0.092	0.454	**-0.450**	< 0.001	-0.069	0.577
	f_{52}	$STS5_{t3}$	2.52	0.981	**0.355**	0.003	-0.167	0.174	-0.094	0.444	**-0.400**	0.001	-0.018	0.882
	f_{53}	$STS5_{t4}$	2.47	0.749	**0.307**	0.011	-0.172	0.161	-0.092	0.457	**-0.371**	0.002	0.033	0.787
	f_{54}	$STS5_{t5}$	2.63	0.858	**0.359**	0.003	-0.190	0.120	-0.049	0.694	**-0.432**	< 0.001	0.014	0.908
	f_{55}	σ_{STS}	0.257	0.271	**0.285**	0.019	-0.106	0.391	-0.070	0.573	**-0.380**	0.001	-0.027	0.828
	f_{56}	$\hat{\sigma}_{STS}$	0.019	0.010	0.210	0.085	-0.037	0.766	0.049	0.692	**-0.272**	0.025	-0.094	0.445
	f_{57}	$Dissim_{STS}$	0.82	0.219	**0.247**	0.042	-0.101	0.411	-0.073	0.555	**-0.288**	0.017	-0.048	0.696
	f_{58}	$STS5_{SVM\ RMS}$	0.233	0.100	-0.224	0.067	0.230	0.060	0.032	0.794	**0.297**	0.014	-0.173	0.159

Task	Feature	Feature Name	Mean	SD	Falls Risk		Knee-extension Strength		Proprioception		Body Sway		MET	
					P	*P*-value	P	*P*-value	ρ	*P*-value	ρ	*P*-value	ρ	*P*-value
STS5	f_{59}	$STS5_{SMA}$	265	82.7	**0.369**	0.002	-0.097	0.432	-0.120	0.328	**-0.276**	0.023	-0.080	0.518
	f_{60}	$STS5_{S1}$	50.600	14.500	**0.269**	0.027	-0.082	0.505	-0.066	0.596	-0.209	0.088	-0.098	0.428
	f_{61}	$STS5_{S2}$	53.700	19.100	**0.463**	0.000	-0.060	0.625	-0.146	0.235	**-0.305**	0.011	-0.212	0.083
	f_{62}	$STS5_{S3}$	51.800	18.000	**0.365**	0.002	-0.089	0.469	-0.125	0.311	**-0.249**	0.040	-0.071	0.563
	f_{63}	$STS5_{S4}$	50.500	16.900	**0.291**	0.016	-0.043	0.730	-0.144	0.241	-0.231	0.058	-0.041	0.740
	f_{64}	$STS5_{S5}$	58.100	20.300	**0.311**	0.010	-0.164	0.181	-0.075	0.541	**-0.275**	0.023	0.042	0.733
	f_{65}	$STS5SMA_{MIN}$	45.100	13.300	**0.302**	0.012	-0.078	0.528	-0.105	0.392	-0.214	0.080	-0.116	0.348
	f_{66}	$STS5SMA_{MAX}$	61.800	21.400	**0.368**	0.002	-0.115	0.349	-0.094	0.446	**-0.301**	0.013	-0.027	0.826
	f_{67}	$STS5SMA_{Range}$	16.700	11.300	**0.344**	0.004	-0.128	0.299	-0.054	0.659	**-0.320**	0.008	0.085	0.493
	f_{68}	$STS5SMA_{Ratio}$	1.370	0.194	0.192	0.116	-0.139	0.257	-0.004	0.973	-0.225	0.065	0.193	0.116
	f_{69}	$STS5SMA_{\sigma}^{2}$	66.800	116.000	**0.288**	0.017	-0.162	0.187	-0.026	0.831	**-0.331**	0.006	0.165	0.180
---	f_{70}	Age	80.000	4.480	0.179	0.144	-0.214	0.080	0.052	0.676	-0.120	0.329	-0.202	0.098
	f_{71}	Sex	---	---	0.082	0.507	**0.587**	< 0.001	0.029	0.817	-0.079	0.521	-0.151	0.218
	f_{72}	RT *z-score*	0.004	0.805	**-0.709**	0.000	0.121	0.324	0.115	0.352	0.237	0.052	**0.350**	0.003

- Units
  - $\{f_1,\ldots, f_6, f_{15},\ldots, f_{24}, f_{49},\ldots, f_{55}\}$ – Seconds
  - $\{f_7\}$ – Hertz
  - $\{f_8,\ldots, f_{14}, f_{29},\ldots, f_{41}, f_{58},\ldots, f_{67}\}$ – g
  - $\{f_{25}, f_{56}\}$ - proportion of task duration
  - $\{ f_{26}, f_{27}, f_{28}, f_{57}\}$ – mean deviation about the mean signal template as a fraction of, the deviation in the mean signal template
  - $\{f_{42}, f_{68}\}$ – ratio of maximum SMA to minimum SMA expended in a cycle
  - $\{f_{43}, f_{69}\}$ – g^2
  - $\{f_{70}\}$ – Years
  - $\{f_{72}\}$ – The reaction time standard score (deviation from the mean reaction time, expressed as a proportion of a standard deviation), unitless

6.3 Modeling

6.3.1 Falls risk models

Table 6.2 shows the performance of linear least-squares models derived using the SFFS procedure (see Chapter 4) using the feature set of 72 features (69 TA-based, 3 non-TA based). Model performance is shown in terms of the Pearson's correlation coefficient, ρ, and its associated *P*-value as well as the root-mean-squared error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{r}_i - r_i\right)^2}$$

between the true values of falls risk, r_i, and their corresponding estimates, $\hat{r}_i$. Models were derived using TA-based features only ($\{f_1, \ldots, f_{69}\}$), non-TA-based features only ($\{f_{70}, f_{71}, f_{72}\}$) and with the entire feature set ($\{f_1, \ldots, f_{72}\}$) . Table II shows the subset of selected features chosen from the set of candidate features for each modeling task.

Figure 6.1-6.3, illustrate the relationship between the true falls risk of each subject and the estimated value, using the selected features (shown in Table 6.2).

TABLE 6.2
FEATURES MAPPED TO FALLS RISK USING VARIOUS FEATURE SUBSETS

Candidate features	Selected Features	ρ	*P*	RMSE
TA-based only	$\{f_{21}, f_{59}, f_{26}, f_{22}, f_5, f_{63}, f_6, f_9, f_{45}\}$	0.541	<0.001	0.809
Non-TA-based only	$\{f_{72}\}$	0.681	<0.001	0.697
All features	$\{f_{72}, f_{17}, f_{22}, f_{21}, f_{25}, f_{16}, f_{57}\}$	0.802	<0.001	0.568

Table 6.3 shows the performance of each of the derived models in indentifying 'at risk' elderly with moderate to high falls risk scores; that is, those with a PPA falls risk score greater than one [17]. The number of true positives $(r_i > 1, \hat{r}_i > 1)$, TP, false positives $(r_i < 1, \hat{r}_i > 1)$, FP, true negatives $(r_i < 1, \hat{r}_i < 1)$, TN and the number of false negatives $(r_i > 1, \hat{r}_i < 1)$, FN, are shown for each falls risk model. Using TP, FP, TN and FN, Table 6.3 also shows the sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV). Interestingly, the falls risk model using the entire feature set does not improve the models performance in identifying at risk elderly.

TABLE 6.3
FALLS RISK MODEL PERFORMANCE IDENTIFYING AT RISK ELDERLY

					Sensitivity	Specificity	PPV	NPV
Falls Risk Model	TP	FP	TN	FN	TP/(TP+FN)	TN/(FP+TN)	TP/(TP+FP)	TN/(TN+FN)
TA-based only	6	6	45	11	0.353	0.882	0.500	0.804
Non-TA-based only	7	5	46	10	0.412	0.902	0.583	0.821
All features	7	5	46	10	0.412	0.902	0.583	0.821

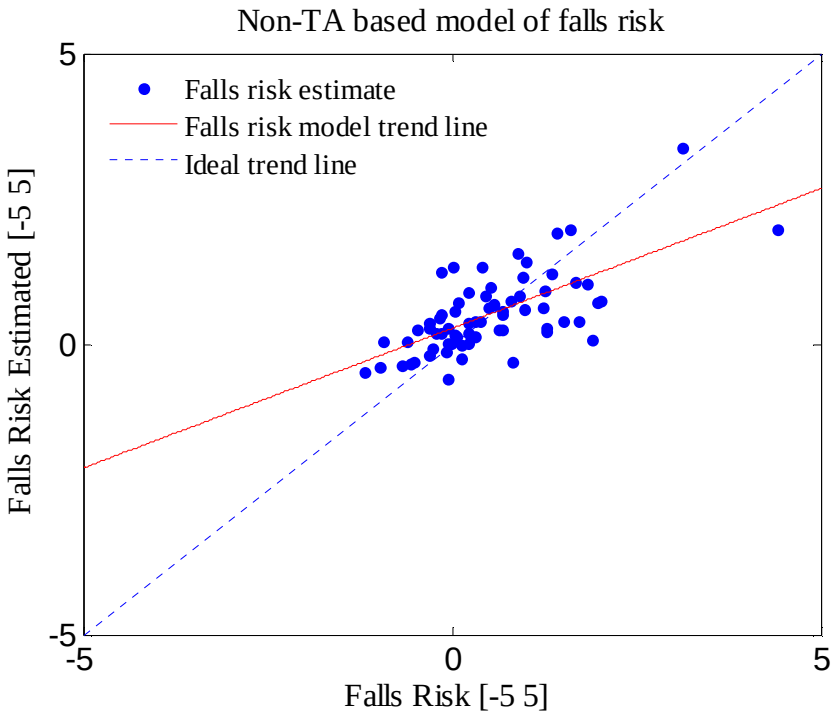


Figure 6.1 - Comparison of estimated falls risk (using selected features $\{f_{72}\}$) versus the true value, as determined using the PPA; RMSE = 0.697, $\rho = 0.681$, $P<0.001$.

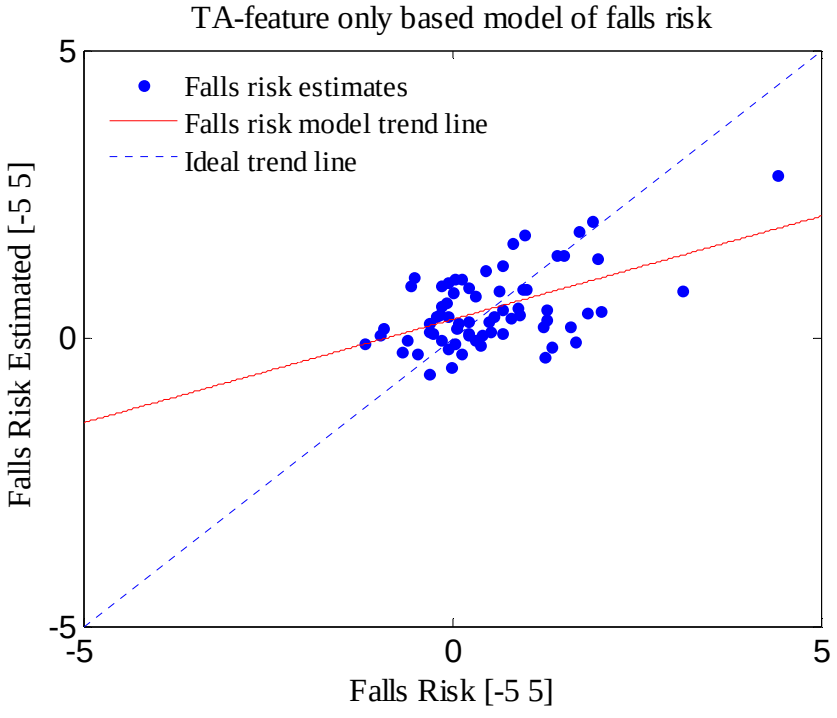


Figure 6.2 - Comparison of estimated falls risk (using selected features $\{f_{21}, f_{59}, f_{26}, f_{22}, f_5, f_{63}, f_6, f_9, f_{45}\}$) versus the true value, as determined using the PPA; RMSE = 0.697, $\rho = 0.681$, $P<0.001$.

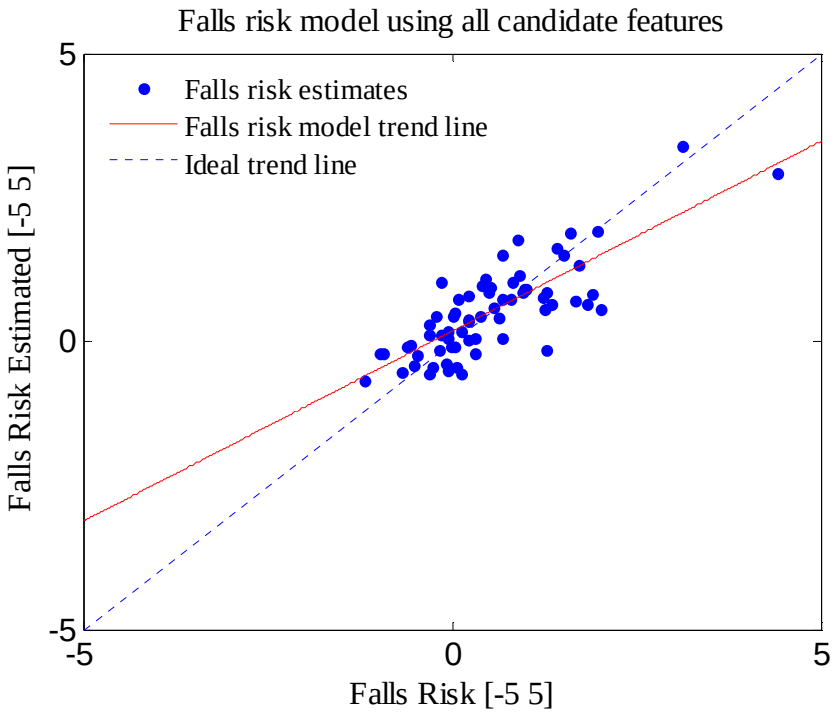


Figure 6.3 - Comparison of estimated falls risk (using selected features $\{f_{72}, f_{17}, f_{22}, f_{21}, f_{25}, f_{16}, f_{57}\}$) versus the true value, as determined using the PPA; RMSE = 0.568, $\rho = 0.802$, $P<0.001$.

6.3.2 Mobility assessment models

Table 6.4 shows the performance of linear least-squares models mapped to four of the PPA subtasks. The table shows the features selected, via the SFFS procedure, to model each of the subtasks. The performance of each model is described in terms of the Pearson's correlation coefficient, ρ, and associated *P*-value as well as the RMSE between the true values for each of subtasks and the model estimates. It should be noted, that models map to the standard scores (*z*-score) for each of the PPA subtasks in which one's performance is centered and scaled to provide the relative performance in terms of the deviation from the expected normal performance. Thus the RMSE represents a fraction of one standard deviation.

Unsurprisingly, *Sex* (f_{71}) was selected as the best feature to map to knee-extension strength given it was the most associated feature (ρ=0.587, P<0.001). Similarly, it is not surprising that the dissimilarity in the trailing-foot steps of the AST, $Dissim_{Trailing}$, the time taken to complete the second AST step, AST_{t2}, and the reaction time standard score, *z-score*, were selected as the best features to map to proprioception, body sway and the MET respectively, as these features were the most associated, (ρ=-0.231, P=0.058), (ρ=-0.466, P<0.001), (ρ=0.350, P=0.003), with each the PPA subtasks. The chosen features for the knee-extension strength test, proprioception test and the MET, include features from each of the DR tasks. Body sway on the other hand, does not include features from the TUGT in its model.

Figures 6.4-6.7, illustrate the relationship between the true values for each of the PPA subtasks modeled and the estimated values, using the selected features shown in Table 6.4. The illustrations highlight the limited performance of the features to model each of the PPA subtasks.

TABLE 6.4
DISTRIBUTION OF FEATURES AND CORRELATION WITH THE PPA

PPA Subtask	Selected Features	ρ	P	RMSE
Knee-extension strength	$\{f_{71}, f_{8}, f_{48}, f_{69}, f_{24}, f_{42}\}$	0.650	<0.001	0.950
Proprioception	$\{f_{27}, f_{7}, f_{2}, f_{56}\}$	0.302	0.012	0.983
Body sway	$\{f_{17}, f_{25}, f_{27}, f_{72}, f_{16}, f_{21}, f_{22}, f_{69}\}$	0.576	<0.001	0.780
MET	$\{f_{72}, f_{68}, f_{58}, f_{7}, f_{16}, f_{17}\}$	0.460	<0.001	0.980

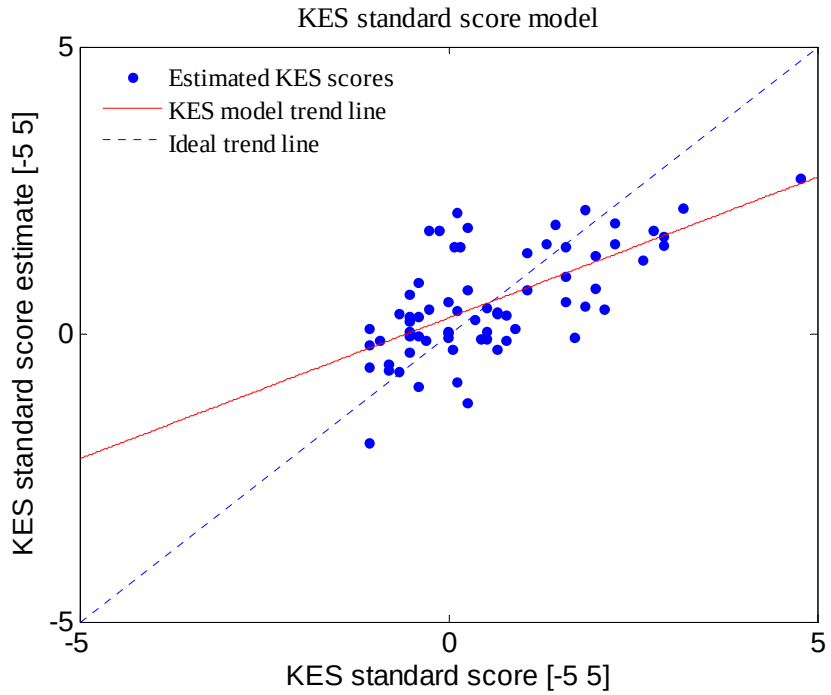


Figure 6.4 - Comparison of estimated KES scores (using selected features $\{f_{71}, f_{8}, f_{48}, f_{69}, f_{24}, f_{42}\}$) versus the true value, as determined using the PPA; RMSE = 0.950, $\rho = 0.650$, $P<0.001$.

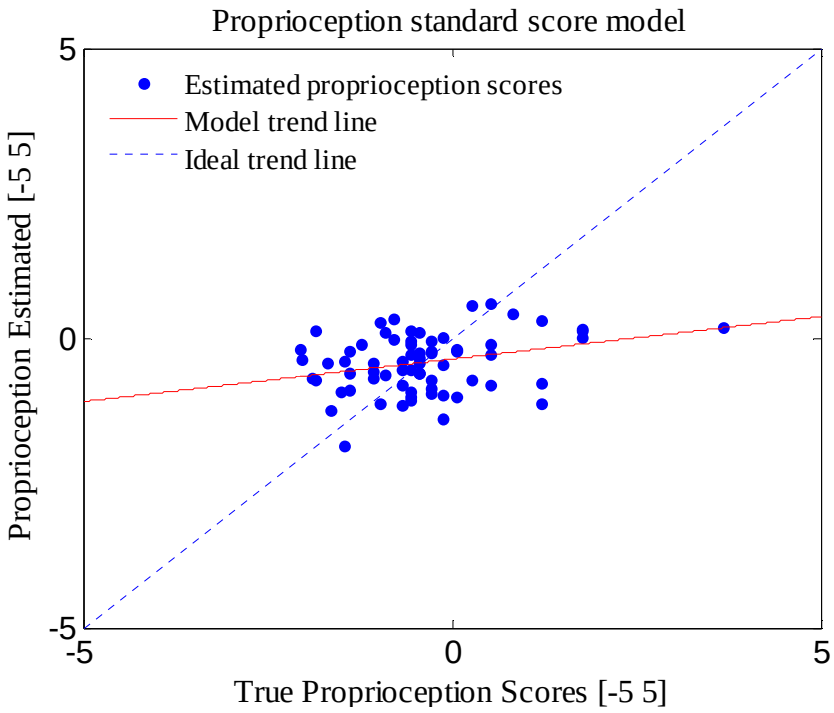


Figure 6.5 - Comparison of estimated proprioception scores (using selected features $\{f_{27}, f_{7}, f_{2}, f_{56}\}$) versus the true value, as determined using the PPA; RMSE = 0.983, $\rho = 0.302$, $P=0.012$.

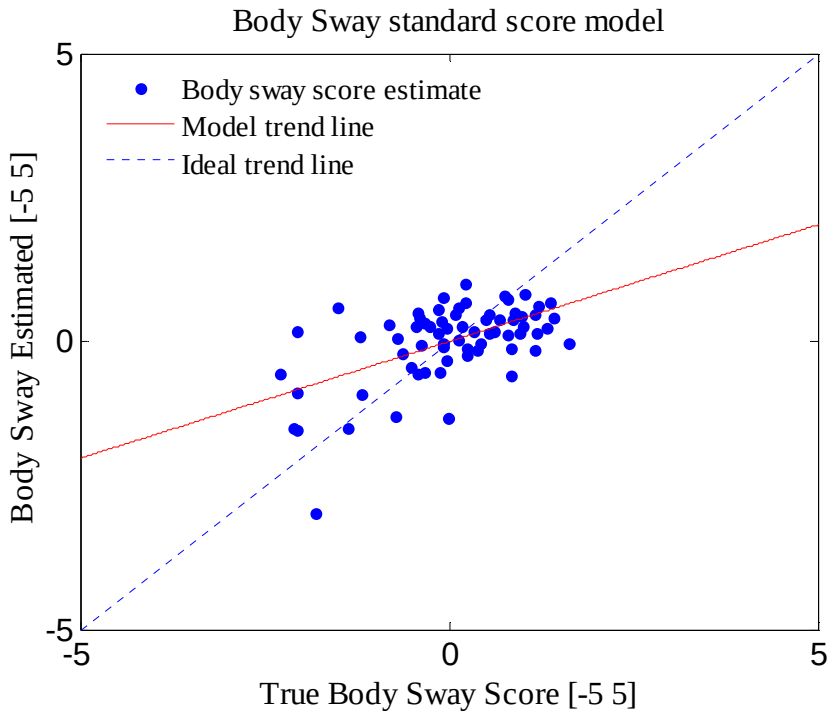


Figure 6.6 - Comparison of estimated body sway score (using selected features {f_{17}, f_{25}, f_{27}, f_{72}, f_{16}, f_{21}, f_{22}, f_{69}}) versus the true value, as determined using the PPA; RMSE = 0.576, ρ = 0.780, P<0.001.

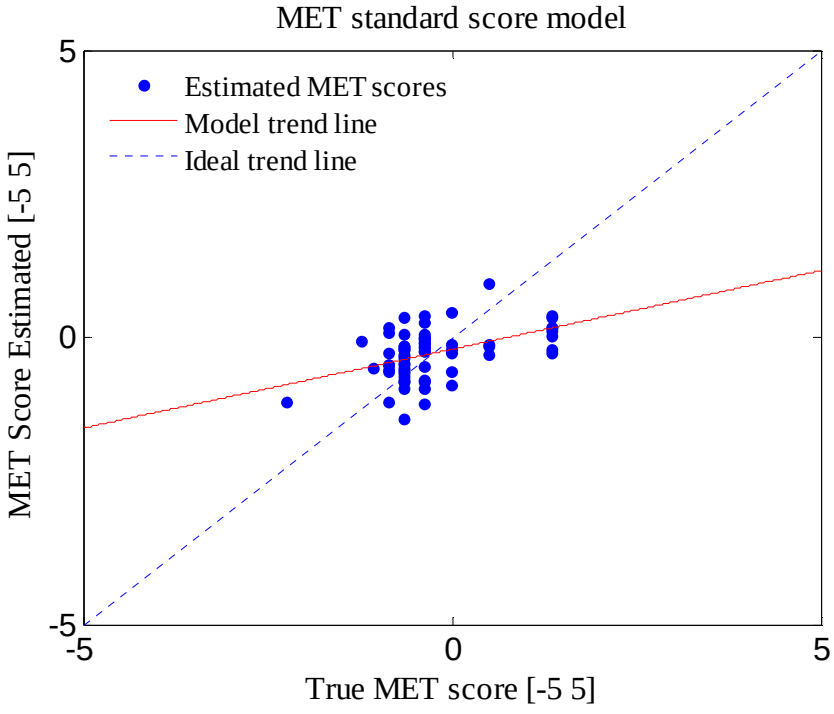


Figure 6.7 - Comparison of estimated MET scores (using selected features {f_{72}, f_{68}, f_{58}, f_{7}, f_{16}, f_{17}}) versus the true value, as determined using the PPA; RMSE = 0.980, ρ = 0.460, P<0.001.

7 Discussion and conclusion

7.1 Discussion

A wearable system for the unsupervised assessment of falls risk and functional ability assessment, using a single waist-mounted tri-axial accelerometer, was designed and evaluated, in a study of 68 community-dwelling elderly. A linear least-squares model of falls risk, using features extracted from a directed routine of movement tasks and simple reaction time, correlated well, with a gold-standard and validated reference for falls risk, the PPA, ($\rho = 0.802$, $P < 0.001$, RMSE = 0.568). Linear least-squares models for known falls risk factors, knee-extension strength, proprioception, body sway and edge contrast sensitivity were derived, using features extracted from the directed routine movements. The correlation and RMSE, between the true risk factor scores and the TA-based models were: ($\rho = 0.650$, RMSE = 0.950, $P < 0.001$), ($\rho = 0.302$, RMSE = 0.983, $P < 0.01$), ($\rho = 0.576$, RMSE = 0.780, $P < 0.001$), ($\rho = 0.460$, RMSE = 0.980, $P < 0.001$), respectively, for the knee-extension strength, proprioception, body sway and Melbourne Edge Test models.

The falls risk model, had a sensitivity and specificity of 41% and 90%, in classifying subjects with moderate to high risk of falls, from those with a low risk of falling. The performance of the falls risk model is reasonable, though the RMSE is a bit high. The models for the risk factors, assessed using the PPA, have a poor to fair correlation with their respective score. All however, have large errors. The models represent standard scores for each of the tasks. An error equal to 1.00, equates to one standard deviation.

An unsupervised assessment of falls risk and functional ability is inherently constrained (see Chapter 4). Directed routine movement selection and the uncertainty in device placement have the most profound effect on the performance of the system. Safety is paramount in an unsupervised assessment. Directed routine movements, regardless of their utility in identifying falls risk or falls risk factors, must be selected on the basis that they can be safely performed unassisted by the elderly. This restriction limits the types of movements that can be included in the directed routine.

The directed routine chosen for evaluation was made up of the STS5, AST and TUGT functional mobility tasks. The movement tasks were chosen with the expectation they would be significantly associated with PPA assessment tasks. The STS5 was expected to serve as a proxy measure for lower-limb strength, the AST, which assesses lateral stability, was expected to relate to body sway, while the TUGT was selected for its associations with all of the PPA assessments.

From the results, a number of features extracted from each of the directed routine tasks, were significantly associated with the PPA falls risk score. However, when considering the associations of the features with each of the PPA assessments, none of the features, from any of the directed routine tasks were associated with proprioception or edge contrast sensitivity (MET) in the sample population of elderly evaluated. A number of features from the TUGT and AST were significantly associated with knee-extension strength and body sway, and features from the STS5 were found to be significantly associated with body sway only. None of the STS5 features evaluated were significantly associated with knee-extension strength. This result was

unanticipated. This can also be seen in the models of each of the PPA assessments. Poor to fair correlations with the PPA assessments were found using combinations of the extracted features.

The solution is simple. Movement tasks that better assess the PPA assessments are needed. Improving the directed routine, to better assess the PPA assessments will improve the performance of the falls risk model and PPA assessment models.

Uncertainty in the placement of the device is the other major limitation in an unsupervised assessment. In an unsupervised, self-administered assessment of falls risk, the wearable device is placed on the body by the user themselves. As such, it is expected that there will be some variability in the placement of device over time. Mathie *et al.* [104], in a pilot study of long-term monitoring, found that the elderly participants tended to vary the placement of the device. Subjects found it important to move the device around to ensure comfort and avoid bruising, with some subjects moving the device every few days. The implication of this is that features extracted from the ambulatory monitor movement data, must be impervious to this variation in placement. As such, features were extracted from signals combining information from all axes of the accelerometer, such as the SVM and energy estimates (see Chapter 5).

A means of ensuring the placement and orientation of the TA enables a better characterisation of movement at the waist, and thus, more information available to be extracted from the signals. Features could reliably be extracted from any of the axes of the accelerometer, something not possible if the orientation and placement of the device is not known. Additional features may improve the model for falls risk and PPA assessment tasks.

The TA is made up of a single tri-axial accelerometer. Numerous studies [101, 108, 117, 120] have combined multiple sensors to evaluate movement using wearable devices. As with ensuring device placement, additional sensors, such as gyroscopes to evaluate rotations, provide more information about the directed routine (DR) movement tasks and thus, the possibility to improve the performance of derived models.

The model for falls risk was derived using features extracted from DR movements, mapped to falls risk scores obtained via the PPA. If a perfect mapping of the PPA were achieved, it would be expected that the TA-based falls risk model would be able to predict multiple fallers with an overall accuracy of between 75-80%, as has been demonstrated in various prospective studies using the PPA [17]. However, the correlation between the TA-based model and the PPA falls risk scores was found to be approximately 80% ($P < 0.001$). The result certainly demonstrates the possibility of evaluating falls risk using wearable monitors such as the TA, but it is unclear how well it predicts elderly fallers from non-fallers. To determine the models predictive abilities, a prospective study in which falls are tracked is required. Alternatively, a reliable falls history, such as the one used by Marschollek *et al.* [141] can be used. For community-dwelling elderly, it is unlikely such an accurate history is available. As such, a prospective study is the most efficient means of obtaining accurate falls data.

The aim of this thesis was to develop an unsupervised assessment of falls risk. A simple directed routine of movements, each of which is feasible for elderly to perform unassisted, enables an unsupervised assessment. From the literature, it is clear there is a need for clinical assessment tools that can discriminate between elderly fallers and non-fallers. Russel *et al.* [47] described

the need for simple, validated multifactorial assessment tools that can be used in busy clinical settings, unlike comprehensive assessments such as the PPA. Clinical assessments need to be simple and quick, in order to be incorporated into busy clinical settings such as a general practitioners clinic. Tiedemann [68] described the requirements for clinical falls risk assessment tools to be feasible for use busy clinical settings. The requirements for the assessment include:

- Quick to administer;
- Simple to administer;
- Require little or no equipment;
- Portable, so that it can be taken to less mobile patients;
- Robust, so that it can be used for multiple patients;
- Acceptable to the elderly, should not cause discomfort;
- Validated;
- Provide information useful for the prescription of intervention.

A TA-based approach has the potential to satisfy these requirements. The DR takes only a few minutes to administer, especially if performed with assistance. The DR requires the device to be placed on waist and a few simple movement tasks to be performed as such, it is definitely easy to administer. Apart from the TA, the DR requires a small platform for the administration of the AST, thus minimal equipment is required and it is therefore quite portable. Like most electronics, the robustness depends on the quality of the enclosure. Enclosures are readily available, that can be attached to the waist that will be sufficiently durable. Mathie *et al.* [104], in a pilot study of long term monitoring, found elderly subjects accepted the TA as a long-term

wearable monitoring device. As such, it is more than reasonable to assume the TA, in its current form-factor, will be acceptable for short-duration monitoring. In terms of aiding the prescription of interventions, the DR has the potential to be able to assess performance in a number of physiological domains, including balance, strength and vision. Measures of balance, strength and vision have been used in a number of randomised control studies to target falls prevention interventions in the elderly [71-72, 78] and achieving reductions in falls rates from between 14-40%. Thus, TA-based assessments of falls risk have the potential to be able to evaluate falls risk in the elderly, but also evaluate risk factors for falls that can be used to target interventions to those that will benefit the most from them.

In comparison with conventional methods of assessing falls risk (see Section 2.3.1), the TA-based approach offers a deterministic assessment that is not affected by inter-rater and intra-rater variability. The TA-based approach combines the discriminatory ability of falls risk screening tools, with the comprehensive evaluation of physical function that full falls risk evaluation provide. Given the falls risk assessment has not been validated, comparisons of the discriminatory ability of the TA-based falls risk assessments and conventional methods using the TUGT, AST, FROP-com or FRST for example, cannot be made. Nevertheless certain comparisons can still be made. The TA-based falls risk assessment involves the assessment of three functional tasks, each of which take less than 30 seconds to perform. As such, the TA-based assessment is very quick to administer. Not quite as fast as the screening tools such as the TUGT, AST, STS, FSST and FTT, that use a single functional task to discriminate between fallers and non-fallers but comparable with other multifactorial screening tools such as the FROP-Com, FRST, EFST and FRAT. The TA-based approach requires the use of a TA, a small

platform to perform the AST and a software utility to gather movement data and evaluate falls risk and physiological function. This means the TA-based assessment is not as simple as questionnaire-based assessments like the FES and ABC but significantly less complicated than screening tools like the FAB, which requires 9 items and a fair amount of setup. A well-designed interface to the TA will make the administration of the assessment as automatic as possible and abstract as much of the complexity of the tool away from the administrator. The biggest difference though, is that the DR-based approach uses purely objective features extracted from the DR movement tasks and is independent of falls status. Conventional multifactorial screening tools use subjective evaluations of balance and functional ability, using mobility assessments or self-reporting, and a self-reported falls history to screen for elderly at risk of falls.

In contrast with the falls risk assessments, evaluated using wearable devices, the approach taken in this work is quite different. Najafi *et al.* [131] used a custom falls risk index combining known risk factors for falls. While parameters extracted from the wearable device discriminated between high risk and low risk groups established with the custom index, classifying falls risk using an assessment not validated means the classification lacks meaning. The likelihood of falling if classified as high risk is unknown. In contrast, the DR-based approach mapped extracted features to a validated assessment of falls risk with a known accuracy in predicting the likelihood of future fall events. In this way, falls risk scores obtained from the DR-based falls risk model provide a clearer indication of the risk of future fall events.

Giansanti *et al.* [135-137] used parameters extracted from an ambulatory monitor attached to the lower back, during assessments of balance on firm and compliant surfaces, to discriminate

between those at high risk of falls and those at low risk of falls as determined by the Tinetti score. The assessment only evaluates parameters related to balance, which is one of a number of independent risk factors associated with falls [1]. The assessment may identify those with balance deficits, but needs to be evaluated to determine how well it identifies elderly fallers. More worryingly, is its incorporation into a remote assessment of falls risk in the elderly. Balance assessed by evaluating body sway on compliant surfaces severely perturbs normal balance and could in fact cause a fall, especially if performed unassisted. In contrast, the DR-based falls risk assessment evaluates a number of movements, relating to multiple physiological domains, and that have been specifically selected for their suitability to be performed unsupervised.

Marschollek *et al.* [141] combined sensory information from the TUGT, using a waist-mounted TA, with parameters from clinical falls risk tools to create a combined model to identify geriatric in-patients likely to fall. The combined model was validated using reliable falls logs maintained by hospital staff. The method of validating the risk assessment model is superior to modeling an existing validated tool. The DR-based falls risk tool is designed as an unsupervised assessment of falls risk in community-dwelling elderly. The model described by Marschollek *et al.* was validated in elderly in-patients. To be used in other elderly populations it would need to be revalidated. This also applies to the classification tree developed by Gietzelt *et al.* [142] which modeled the STRATIFY falls risk tool, which is used to identify elderly in-patients likely to fall.

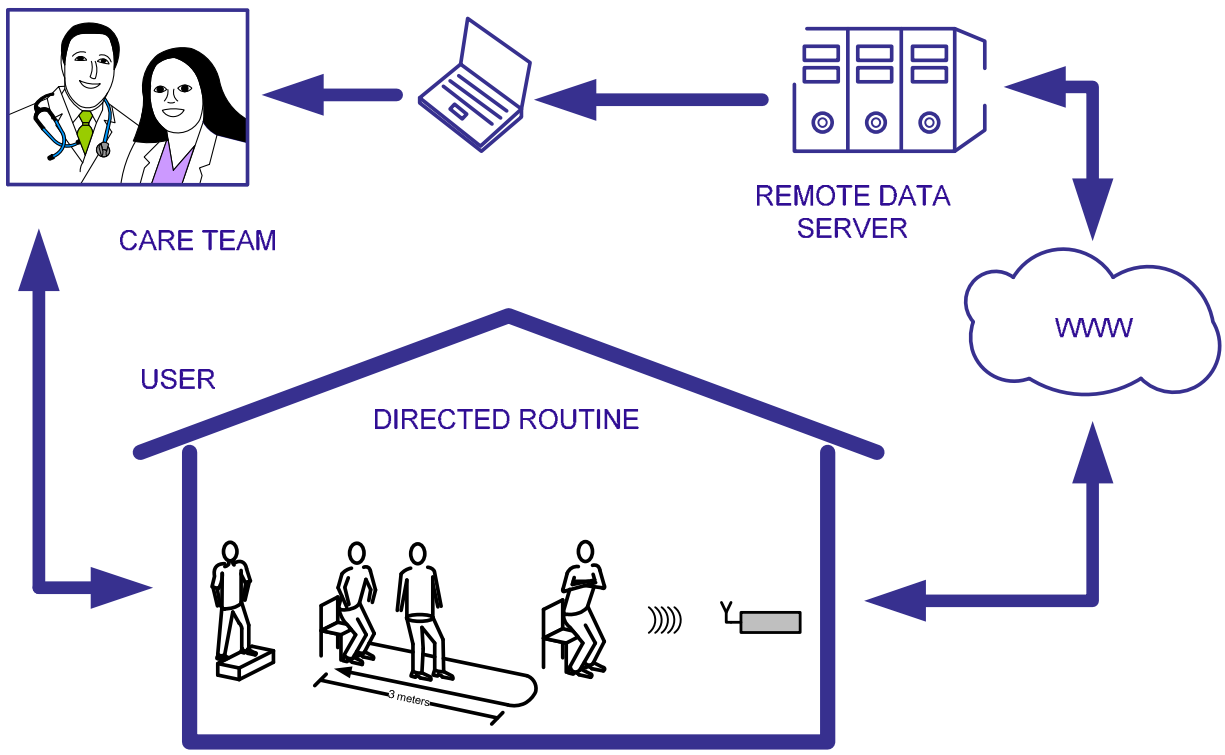


Figure 7.1 - Falls management system architecture.

The models for falls risk and physiological function derived from the DR acceleration data form a means for assessing falls risk and physiological function unsupervised and unassisted. However, the DR forms only one a single component of a system needed to fully deliver an unsupervised assessment. Figure 7.1 shows a possible model for the long-term management of falls in the elderly. Data from the DR is uploaded to remote servers for analysis. Care providers, via an external computer, can access the data record for patients. This provides a longitudinal record of falls risk and physiological function.

Within the home, an intuitive way of implementing the DR is required, which guides the elderly subjects through the DR and uploads collected data to a remote server for processing. Chapter 3

describes a home monitoring system made up of the wearable TA and Portal, which collects the TA data. The TA, via a series of beeps guides subjects through each movement in the DR. While beyond the scope of work of this dissertation, the system is currently being trialed in a cohort of elderly subjects to evaluate feasibility and acceptability.

More interesting is what is required on the remote server to be able to implement an unsupervised assessment of falls risk. Quality indices, to provide some certainty that collected data contain DR data are required. If falls risk and physiological parameters extracted from the data are ultimately used to make clinical decisions, collected data must be checked to ensure it actually contains DR movements. Uncertainty in remotely collected data is the fundamental limitation. In addition to quality metrics, automatic segmentation algorithms must be derived to segment the DR movement tasks into each of the phases so that, features required for each of the models can be evaluated.

Longitudinal records of falls risk and parameters such as visual acuity, lower-limb strength and balance need to be reported to caregivers so that decisions can be made to manage falls risk. Changes over time in falls risk, balance, vision, proprioception and lower-limb strength can be used to manage interventions to reduce ones risk of falls.

7.2 Conclusion

An unsupervised assessment of falls risk and physiological function was developed using the data from a directed routine of movement tasks using a single, waist-mounted tri-axial accelerometer. Falls risk was modeled against a validated falls risk assessment, the PPA. The model correlated well with PPA however, the TA-based falls risk model must be evaluated using reliable falls data in order to truly determine its predictive accuracy. Models for knee-extension strength, proprioception, edge contrast sensitivity and body sway were similarly derived. These models showed poor to fair correlations with the scores from the PPA assessment, suggesting the chosen DR tasks were not able to completely characterise these physiological functions. A more appropriate selection of DR movements may improve falls risk models as well as models for physiological functions. What is clear, is the potential for simple wearable monitors to evaluate falls risk and identify those at increased risk of falling, as well as, identify risk factors for falls that can be used to target appropriate interventions to reduce the risk of future falls. Moreover, systems can be developed to enable unsupervised assessment of falls risk, enabling longitudinal tracking of falls risk and functional ability that is not possible via conventional methods for falls risk assessment. Improved management of falls reduced the risk and rates of falls in the elderly. The implications are profound. Falls come at a tremendous cost to the healthcare system. Methods that can reduce the incidence of falls enable limited funds to be better utilised in other areas of healthcare. Falls are a major cause of morbidity and mortality in the elderly. Falls are a major risk factor for institutionalisation and often lead to heightened fear which causes restriction in activity and overall reduction in quality of life. Methods that can reduce ones risk of falls thus play a significant role in providing better quality of life in the elderly.

Papers arising from this thesis

1. M. N. Narayanan, S. R. Lord, M. M. Budge, B. G. Celler, and N. H. Lovell, “Falls Management: Detection and Prevention, using a Waist-mounted Triaxial accelerometer,” presented at the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, France, 2007.

2. M. N. Narayanan, M. E. Scalzi, S. J. Redmond, S. R. Lord, B. G. Celler, and N. H. Lovell, “A Wearable Triaxial Accelerometry System for Longitudinal Assessment of Falls Risk,” presented at the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vancouver, Canada, 2008.

3. M. N. Narayanan, M. E. Scalzi, S. J. Redmond, S. R. Lord, B. G. Celler, and N. H. Lovell, “Evaluation of Functional Deficits and Falls Risk in the Elderly – Methods for Preventing Falls,” presented at the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Minneapolis, Minnesota, 2009.

4. M. N. Narayanan, M. E. Scalzi, S. J. Redmond, S. R. Lord, B. G. Celler, and N. H. Lovell, “Longitudinal Falls-Risk Estimation Using Triaxial Accelerometry,” *IEEE Trans. Biomed. Eng.*, vol. 57(3), pp. 534-541, 2010.

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Appendix

A.1 – Human Ethics forms

THE UNIVERSITY OF NEW SOUTH WALES

Graduate School of Biomedical Engineering

PARTICIPANT INFORMATION STATEMENT

Falls Detection Using a Tri-axial Accelerometer

You are invited to participate in a study on ambulatory monitoring using a small wearable device. This device will help us record data relating to your postural sway and balance (how well you can stand and walk without feeling unsteady). We also hope the data collected will help us develop ways of identifying falls and stumbles.

The study will be conducted over a period of up to 8 weeks. The tri-axial accelerometer will measure and record how you move around as you go about your usual daily activities.

As an attendee of the POWMRI falls clinic you have been identified as a potential participant in this study.

At the commencement and conclusion of the study you will be **asked** to complete an assessment of your balance and fall risk, and may be asked for relevant information on your medical history.

For the duration of the study, you will be **asked** to attach the tri-axial accelerometer to your waist belt when you get up in the morning. You will be **asked** to wear the tri-axial accelerometer throughout the day until you go to bed, except when bathing or showering. Once a day you will be **asked** to complete a fixed routine of movements involving sitting, standing, walking, and lying. For the duration of the study, you will also be **asked** to maintain a daily log of any falls or stumbles you experience, noting an approximate time of the event. At the conclusion of the trial you will be **asked** to complete a small questionnaire on your evaluation of the system. It is expected that the daily log will take you approximately 5 minutes to complete each day. Similarly, the post trial questionnaire is expected to take about 5 minutes to complete.

If you decide to participate, you will be given a tri-axial accelerometer and data logger for the duration of the study. Data collected by the tri-axial accelerometer is transmitted to a small

data logger where it will be stored for the duration of the trial. All equipment and its installation will be provided to you free of charge. A technical support line will be available to provide you with technical support if required.

It should be noted participation is completely voluntary and your decision whether or not to participate 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 at any time without prejudice.

The technology for this project is being supplied by MedCare Systems Pty. Ltd. It should be noted that two of the Chief Investigators (Prof Nigel Lovell and Prof Branko Celler) are Directors of MedCare Systems.

Complaints may be directed to the Ethics Secretariat, The University of New South Wales, SYDNEY 2052 AUSTRALIA (phone 9385 4234, fax 9385 6648, email ethics.sec@unsw.edu.au). Any complaint you make will be treated in confidence and investigated, and you will be informed of the outcome.

The safety and security of your information is a high priority to us, and every effort is made to ensure your privacy. Your information will be accessible only by yourself, and named research staff at the UNSW. If you give us your permission by signing this document, we plan to discuss/publish research data gathered from the results of the study, provided that you cannot be identified.

If you have any questions, please feel free to ask us. If you have any additional questions later, Michael Narayanan (9385 5866, 0419 225 001) or Prof Nigel Lovell (9385 3922) will be happy to answer them. You will be given a copy of this form to keep.

THE UNIVERSITY OF NEW SOUTH WALES

Graduate School of Biomedical Engineering

CONSENT FORM

Falls Detection Using a Tri-axial Accelerometer

You are making a decision whether or not to participate. Your signature indicates that, having read the Participant Information Statement, you have decided to take part in the study.

.....	.....
Signature of Research Participant	Signature of Witness
.....	.....
(Please PRINT name)	(Please PRINT name)
.....	.....
Date	Nature of Witness

.....
Signature(s) of Investigator(s)

.....
Please PRINT Name

THE UNIVERSITY OF NEW SOUTH WALES

Graduate School of Biomedical Engineering

REVOCATION OF CONSENT

Falls Detection using a Tri-axial Accelerometer

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.

....
Signature Date

.....
Please PRINT Name

The section for Revocation of Consent should be forwarded to Michael Narayanan, School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, NSW 2052.