Simulation of a wireless sensor network for unobtrusively detecting falls in the home

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Simulation of a Wireless Sensor Network for Unobtrusively Detecting Falls in the Home

by

Arni Ariani

A thesis submitted in partial fulfillment for the degree of Doctor of Philosophy

in the

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One serious issue related to falls among the elderly living at home or in a residential care facility is the 'long lie' scenario, which involves being unable to get up from the floor after a fall for 60 minutes or more.

The first part of this thesis focuses on developing algorithms for unobtrusive falls detection using simulated responses from passive infrared (PIR) and pressure mat (PM) sensors, aimed at older subjects living alone at home. A Java-based wireless sensor network (WSN) simulator was developed. This simulation reads the room coordinates from a residential map, a path-finding algorithm (A*) simulates the subject's movement through the residential environment. The fall detection algorithm was tested on 15 scenarios; three scenarios of ADL, and 12 different types of falls (four types of fall, each with three post-fall scenarios). A decision tree-based heuristic classification model is used to analyse the data and differentiate falls events from normal activities. The accuracy of the algorithm is 62.50%.

The second part of this thesis focuses on addressing three remaining drawbacks of the previous algorithm and improving the robustness of the system. To solve the problem of the person continuing to move after falling, the potential effectiveness of using two PIR sensors at each location (which monitor the upper and lower halves of the room) is investigated. Graph theory concepts are used to infer how many people (or groups) are present in the environment, loosely track their movement/location, and monitor them independently for falls. This graph representation is also used to identify when someone leaves the residence. A revised fall detection algorithm, also based on a heuristic decision tree classifier model, is tested on 15 scenarios, each including one or more persons; three scenarios of ADL, and 12 different types of falls. The accuracy of the algorithm is 89.33%.

Future work will focus on the investigation of the impact of using a more realistic (suboptimal) sensor characteristic on the performance of the designed fall detection algorithm, the fabrication of a hardware prototype and the preliminary implementation of this fall detection system in either a laboratory or real-world environment.

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THE UNIVERSITY OF NEW SOUTH WALES

Abstract

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Doctor of Philosophy

by Arni Ariani

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The first part of this thesis focuses on developing algorithms for unobtrusive falls detection using simulated responses from passive infrared (PIR) and pressure mat (PM) sensors, aimed at older subjects living alone at home. A Java-based wireless sensor network (WSN) simulator was developed. This simulation reads the room coordinates from a residential map, a path-finding algorithm (A*) simulates the subject's movement through the residential environment. The fall detection algorithm was tested on 15 scenarios; three scenarios of ADL, and 12 different types of falls (four types of fall, each with three post-fall scenarios). A decision tree-based heuristic classification model is used to analyse the data and differentiate falls events from normal activities. The accuracy of the algorithm is 62.50%.

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I want to express my love and appreciation for my family. My parents who have given me so many opportunities that have allowed me to accomplish this educational goal. My lovely husband and son, I cannot thank you enough for your support and love during my studies.

I would like to say thank you to the government of Indonesia and Ministry of Communication and Information Technology of the Republic of Indonesia for granting me a scholarship so that I could continue my education to PhD level.

Finally, and most importantly, is Thanks to Allah (the Lord of the Universe) who gave me the strength and guidance to complete this journey.

Contents

Abbreviations

2D	two dimensional
3D	three dimensional
6MWD	six-minute walking distances
ABA	acceleration based algorithm
ADL	activity of daily living
ANOVA	analysis of variance
BBS	Berg balance scale
BMI	body mass index
C	falls with consciousness
CI	confidence interval
CAD	computer-aided design
COP	centre of pressure
DOM	document object model
ECG	electrocardiogram
EMG	electromyogram
FN	false negative
FP	false positive
GMM	Gaussian mixture model
GPS	global positioning system
GSM	global system for mobile communications
GUI	graphical user interface
HMM	hidden Markov model
iDorm	intelligent dormitory

MAC	media access control
MEMS	microelectromechanical systems
N	normal activity
OCA	orientation change algorithm
PD	Parkinson's diseases
PDA	personal digital assistant
PIR	passive infrared
PM	pressure mat
R	falls followed by recovery
PR	prevalence ratio
RFID	radio-frequency identification
ROC	receiver operating characteristic
RSSI	received signal strength indicator
RTLS	real-time locating system
SD	standard deviation
SDAT	senile dementia form of the Alzheimer's type
SE	standard edition
SMS	short message service
SGA	subjective global assessment
SVG	scalable vector graphics
SVM	support vector machine
TBI	traumatic brain injury
TN	true negative
TP	true positive
UK	United Kingdom
US	United States of America
Wi-Fi	wireless fidelity
WSN	wireless sensor network
WiMAX	worldwide interoperability for microwave access
XML	extensible markup language
U	falls with unconsciousness
URI	uniform resource identifier

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Patent and Papers

In August 2012, a provisional Australian patent titled "Unobtrusive fall detection in the presence of one or more people" containing the general approach and methodology of this research work was filed, under the application number 2012903367.

Part of the content of this work has also been published in the following refereed works:

- A. Ariani, S.J. Redmond, D. Chang, and N.H. Lovell, "Software simulation of unobtrusive falls detection at night-time using passive infrared and pressure mat sensors," in *Proceedings of the 32rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2010, pp. 2115-2118.
- A. Ariani, S.J. Redmond, D. Chang, and N.H. Lovell, "Simulated unobtrusive falls detection with multiple persons," *IEEE Transactions on Biomedical Engineering*, 2012 (in press).

Chapter 1

Introduction

1.1 Research motivation

Along with many other developed countries, Australia is experiencing a "greying population" or an "aging population" (Table 1.1). In 2010, 13.5% of 22.2 million people were aged 65 years or older and it is projected that by the year 2050 this group will account for 22.7% of the forecast population of 35.9 million people [1]. This demographic trend reveals a number of issues, including social and economic

Table 1.1: The past and an estimate of future population trends in Australia for the period from 1970 to 2050. The population data is presented in millions of people [1].

Age range	**1970**	**2010**	**2020**	**2030**	**2040**	**2050**
0-14	3.6	4.2	4.9	5.4	5.7	6.2
15-64	7.9	15.0	16.6	18.2	20.0	21.6
65-84	1.0	2.6	3.7	4.8	5.6	6.3
85 and over	0.1	0.4	0.5	0.8	1.3	1.8
Total	12.5	22.2	25.7	29.2	32.6	35.9
Percentage of total population						
0-14	28.8	19.1	19.0	18.3	17.4	17.2
15-64	62.8	67.4	64.7	62.4	61.3	60.2
65-84	7.8	11.7	14.3	16.6	17.2	17.6
85 and over	0.5	1.8	2.1	2.7	4	5.1

problems as the ratio of caring (the ratio of people aged between 15-64 to those aged 65 years and above) is getting smaller [1].

This trend also indicates that there will be an imbalance between the availability of carers and the service demands for dependent older people, as well as a decline in the ratio of tax-paying employees (who are the primary contributors to health services funding) to older people (who are high consumers of health care services) [1]. This problem may be exacerbated by the fact that elderly people tend to have higher demands of health services when compared to any other population groups (Figure 1.1) [1].

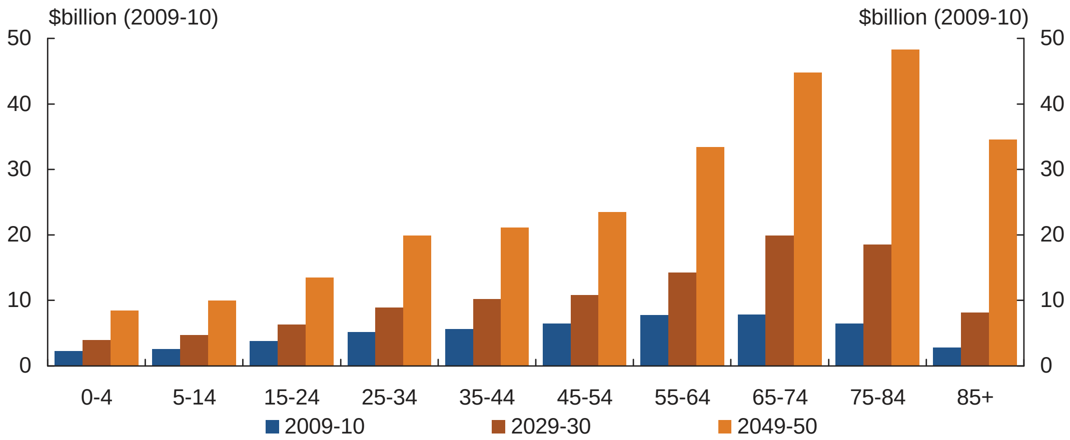


FIGURE 1.1: The allocation of health care funds for period 2009 - 2050 across all age groups [1].

Research has determined that falls and their related injuries have become a leading cause of increasing morbidity, disability and health care expenditure [2]. Approximately one out of every three people aged 65 years or older experience at least one fall every year [3, 4]. Figures in the United States showed that 49% of 6712 falls in men aged over 65 years and 55% of 15845 falls in women aged over 65 years resulted in minor injuries such as lacerations, abrasions and sprains, while fractures occurred in 29% of 6712 falls in men to 38% of 15845 falls in women [5].

In Australia, unintentional falls are a leading cause of death from injury in men and women aged 70 years and older [6], constituting 26.52% of the 9,775 injury related death cases reported in 2004-05. Death rates due to falls was higher among women in the age groups of 70-74 and 80-84 years [6]. Moreover, the huge burden of fall injuries is seen not only in the number of fatal injuries, but also in the increase in fracture-related injuries, as the number and percentage of recorded hospital admissions rose slightly for people aged 65 years and over; increasing from 60,497 of 123,461 falls (49%) in 2003-2004 [7] to 66,784 of 132,566 falls (50.38%) in 2005-2006 [8] .

A 2005-06 report by the Australian Institute of Health and Welfare estimated that the cost of short-stay hospital admissions due to falls has reached AUD$566 million, and additional lifetime health care costs related to injurious falls have increased to more than AUD$1 billion per annum [9].

A fall can have an associated 'long lie' scenario, which occurs when a subject is unable to right themselves from the floor without help after experiencing a fall, and subsequently remains on the floor for at least 60 minutes [10]. Older people who experienced this long lie scenario could face serious consequences; for instance, psychological trauma (fear of falling, which may lead to limited activity) [10] and physical trauma (hypothermia, bronchial pneumonia and pressure sores) [11]. Any of these situations could put the person's life in danger, irrespective of whether they had a serious fall-related injury.

Findings from one study showed that 15% of older fallers were found lying on the floor for more than one hour [12]. One of the solutions to this problem is to automatically identify the occurrence of a fall as soon as possible and subsequently generate an emergency notification signal to summon help. Most research currently focuses on the use of wearable sensors to differentiate falls from activities of daily living (ADLs) [13, 14] and to trace individuals moving through indoor environments [15, 16]. **However, older people tend not to use such devices due to comfort issues, the belief that it has become a symbol of frailty, or simply due to forgetfulness (which is particularly problematic for those suffering from dementia [17]), or because they have gotten out of bed in the middle of the night to go to the bathroom and fail to affix the device.**

Based on these and other reasons, recent research themes have evolved in the direction of developing a smart home or residence, often using an optimised number of ambient sensors for unobtrusive detection of falls. **However, so far this stream of research has focused exclusively on unobtrusive monitoring systems**

that are developed to cope with one individual in the home environment at a time [18, 19].

Furthermore, the reliability of unobtrusive monitoring systems depends on many factors, including the hardware configuration, the number of sensors and the placement of these sensors. **Since the development of hardware is time consuming and costly, the use of simulated environments and smart home solutions can be considered as a cost-effective means to support the hardware development.** By using a simulated environment, the required hardware specification can be determined and further reduce the amount of time needed for hardware prototyping.

In summary, little work has been performed towards the analysis and development of algorithms that can unobtrusively track the movement of multiple people and detect falls when they occur with the intent of reducing the number of long lie scenarios.

1.2 Objectives

With the highlighted motivation in the previous section, the work contained in this thesis aims to achieve the following major objective:

- To investigate, by means of simulation, the potential effectiveness of wireless ambient sensors to unobtrusively monitor older people and raise an alarm if a fall is detected, without having to use wearable devices, and furthermore to do this in the presence of multiple persons present in the same environment.

1.3 Thesis contributions

The contributions of this thesis are:

- This thesis aims to contribute to promoting the development and use of unobtrusive monitoring systems by using simple motion sensors, combined with load sensors on furniture to infer if somebody has fallen.

- This thesis presents a technique incorporating the use of graph theoretical concepts for simultaneously inferring the number of people in the environment, tracking their movement/location, and monitoring them independently for falls.
- An algorithm is developed and validated through simulation, demonstrating the ability to detect falls unobtrusively without requiring users to wear a sensor or alarm, and with support for multiple people present in the same environment.

1.4 Thesis organisation

The remainder of the thesis is organised as follows:

Chapter 2 presents a literature review, which includes the latest approaches used in falls detection technologies and the pros and cons of the different principles and approaches used for fall detection. It also summarises the challenges that this technology needs to overcome in order to enter consumer and industrial markets.

Chapter 3 provides details of the software development process, including a wireless sensor network (WSN) map editor and WSN simulator. The WSN map editor is used to create and save different types of floor plans, including existing furniture or appliances and to add ambient sensors in a 2-dimensional (2D) model. The WSN simulator provides the ability to simulate the resident's movement through the residential environment, as defined by the 2D model, and monitor how ambient sensors respond in a binary (on/off) manner to the resident's movement.

Chapter 4 uses a WSN simulator to investigate the usefulness of unobtrusive ambient sensors to detect falls. These sensors consist of passive infrared (PIR) and pressure mat (PM) sensors placed at various vantage points throughout the residential unit to detect falls and identify the location where the fall occurs.

Chapter 5 investigates the usefulness of simulated responses from the PIR sensors (which independently monitor the upper and lower halves of the room) and PM sensors to unobtrusively track the movement of multiple people and detect falls when they occur.

Chapter 6 summarises the work presented in this thesis and discusses some potential future improvements in the implementation of an unobtrusive monitoring system for fall detection in older people.

Chapter 2

Background

2.1 Introduction

An aging population is a common challenge faced in many developed countries. Globally, the population of people aged 65 years or over is estimated to exceed 1.5 billion by 2030 [20]. According to 2009 data in the European Union, the population of people over 65 years of age has exceeded more than 148 million [21]. Based on 2010 data in the United States, the population of people over 65 years has reached more than 39 million [22].

In 2009, the life expectancy at birth in Australia was 84 years for men and 87 years for women. Consequently, there are over 2.9 million people aged 65 and older in Australia [23]. By 2041, there will be over 5.4 million Australian's aged over 65 years. This number represents an increase of 3.4 million or 166% over the base population in 1993. This "greying population" has caused the Australian government to consider the burden on the health system and the need for better management of resources that are currently used very inefficiently for this older population group [24].

Older people are living longer and more fulfilled lives, and naturally they desire to live as independently as possible. However, independent lifestyles come with risks and challenges. Falls and their related injuries are a major source of morbidity and disability, and raise costs for health care facilities [2]. In general, over one third of people aged 65 years or more experience at least one fall every year [2, 3]. Findings from a survey in United States also showed that more than 35.6% of falls resulted in fractures [5]. The head and the neck are the most common parts of the body which are injured when a person experiences a fall. The rates of injuries were also high for the lower trunk (23.2%) and arm/hand (17.3%) [5]. Furthermore, falls can also lead to other serious consequences such as fear of falling, which can cause restricted activity [25].

In the United States, unintentional falls were a major cause of injury related death in 2005. A typical mild traumatic brain injury (TBI) or concussion that commonly results from a fall is classified in three grades. In grade one or two, the subject does not lose consciousness and can seek help [26]. Whereas, grade three includes unconsciousness and hence an inability to seek help. If a subject experiences 30 minutes or less of losing consciousness, their injuries can be classified as mild categories [26]. There were 7,946 deaths caused by TBI. Furthermore, 56,423 people were admitted to hospital due to TBI as a result of falling. The report also shows that the average price for hospital care related to TBI was $19,991 and $16,006 for men and women, respectively [27].

A fall can have an associated long lie scenario, which is an inability to get up from the floor without assistance, and the subject subsequently remaining on the floor for a period of one hour or more [10]. A number of studies report on the association of a long lie scenario with the correlation between the waiting time before intervention and the morbidity/mortality rate [28, 29].

According to a Pew Research Center analysis of 2008 census data, there has been a rise in the number of older people living alone (34.4% of women and 17.9% of men) in the United States. There are a couple of factors that contribute to this, including an increase in life expectancy for older people and a decrease in shared living arrangements. Currently, the life expectancy in America is 91.1 years for men and 92.2 years for women. Moreover, the number of older people living with their families has also declined, mirroring this trend [30]. Given the fact that more and more older people choose to stay inside the house for longer, it is anticipated that the rate of fall occurrences and long lie scenarios may increase accordingly.

Table 2.1 presents the occurrence rates of falls and long lie scenarios for older people over 90 years old living in Cambridge, England [12]. Findings showed that more than

81.8% of falls occurred when people were alone. In all, 265 falls were reported, of which 40 (15.1%) resulted in the long lie scenario (remaining on the ground for more than one hour), although when looking across all falls, 176 (66.4%) needed assistance getting up from the floor. The most common setting for these long lie scenarios is in sheltered housing (17/62, 27.4%), possibly due to increased frailty relative to their community-dwelling peers and reduced supervision compared to those in fully institutionalised care. The second highest rate occurs in the community (16/120, 13.3%). There was no reported information for 16 of the 265 falls.

TABLE 2.1: The percentage rates of falls in different environments [12].

	Community (n=120)	**Sheltered housing (n=62)**	**Institutional settings (n=83)**	**All (n=265)**
Alone when experiencing a fall	93 (77.5%)	58 (93.6%)	66 (79.5%)	217 (81.9%)
Unable to get up without assistance	52 (43.3%)	41 (66.1%)	83 (100%)	176 (66.4%)
Time on floor $\leq$1 hour	97 (80.8%)	40 (64.5%)	72 (86.8%)	209 (78.9%)
Time on floor $\geq$1 hour	16 (13.3%)	17 (27.4%)	7 (8.4%)	40 (15.1%)
Time on floor unknown	7 (5.8%)	5 (8.1%)	4 (4.8%)	16 (6.1%)

In more than 98.5% (141/143) of falls that occurred when people were alone and unable to get up, an alert system was in place [12]. However, findings also showed that only 28 of 143 older people managed to receive assistance by pressing the alert button after a fall (Figure 2.1).

Naturally, the preferred proactive solution to prevent long lies from occurring is to prevent a preceding fall from occurring [31]. This is an onerous multifactorial

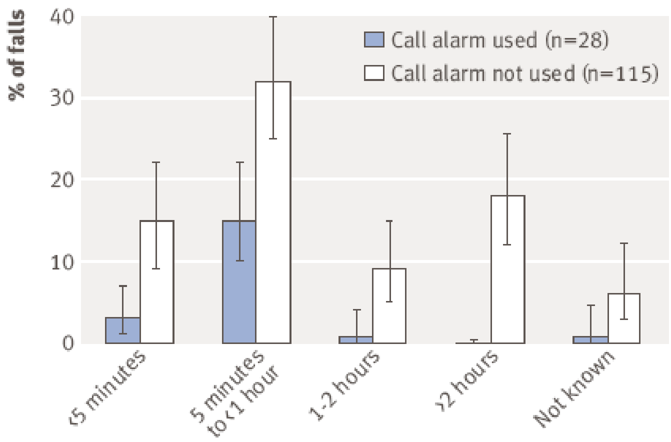


FIGURE 2.1: The relation between the duration of time spent lying down on the floor and the use of a call alarm to summon help. This data is presented with 95% confidence intervals (CIs) [12].

challenge which is attracting much research attention, but progress is slow. The next most appropriate means to address this problem is to automatically recognise the fall as soon as possible after it happens and subsequently send an emergency call to summon help.

Comprehensive reviews of fall detection technologies have been published in the literature [32–35]. Perry [36] reported a relatively short but comprehensive evaluation of sensor approaches for real-time falls detection and highlighted the pros and cons of different approaches. A few books have been released by researchers in this area, such as Brownsell et al. [37] who focussed on technologies that can prevent, detect and predict falls. This particular book evaluates the use of wearable and ambient sensors to detect falls. It also lists advantages and disadvantages of each approach.

This chapter starts by describing the epidemiology of falls. Designing a fall detection system that aims at decreasing the causes of fall (both intrinsic and extrinsic) requires researchers to look more deeply into the sources of the fall, including environmental, behavioural, as well as physiological factors [10]. This chapter also reports on the state-of-the-art in fall detection, expectations of these technologies and pros and cons of different principles and approaches of fall detection. We also summarise the challenges that this technology needs to overcome in order to identify and facilitate priority research in this field.

2.2 Epidemiology of falls

One important step towards developing a workable system for the detection of falls is to learn what factors lead to falls and to characterise the various phases of falling. In this section, the epidemiology of falls including the definition and stages of a falls are described.

2.2.1 What is a fall?

The definition of a fall by the Kellogg international working group on the prevention of falls in the elderly in 1987 was “unintentionally lying down on the floor, or particular lower level which is as a result of a violent knock, loss of consciousness, paralytic stroke (sudden onset of paralysis resulting from injury to the brain or spinal cord) or an epileptic seizure" [38]. This definition has been applied in numerous research studies and subsequently extended to add falls that occur from other causes, such as dizziness and vertigo as additional common causes of falls [39], syncope as a risk factor for falls-related injuries [40] and other effects of physical changes for instance neurologic (transient ischaemic attacks, gait disorders) or cardiovascular (hypotension, hypertension), which can result in falls [41].

Other definitions of a fall include a rapid change in body posture from an upright position while sitting or standing to a reclining or almost lying position, with the transition between these postures not being controlled [42].

According to the definitions above, any automatic fall detection device must detect falls in older people, either caused by natural or environmental factors. Another feature required of a fall detection system is the capability of differentiating a fall from other movements performed intentionally.

2.2.2 Phases or stages of a fall

There are four phases of falls: the pre-fall phase, the critical phase, the post-fall phase and the recovery phase [43]. The first phase of a fall (the pre-fall phase) is characterised by occasional sudden movements when doing daily living activities.

This is followed by the second phase of the fall (the critical phase), which is the abrupt fall of the body to the ground with a vertical shock at the end. In this second phase, the duration is particularly short (around 200 to 300 ms) [44].

The third phase of the fall (the post-fall phase) is described as a situation when the subject is inactive (e.g. lying down motionless on the floor).

The last a phase of a fall (the recovery phase) is described as the ability to stand up after a fall with or without assistance.

Most of research for detecting falls attempts to detect the moment the fall occurs (the critical phase), rather than the scenario of inactivity resulting from the fall (the post-fall phase), which will be our proposed method for the development of falls detection system.

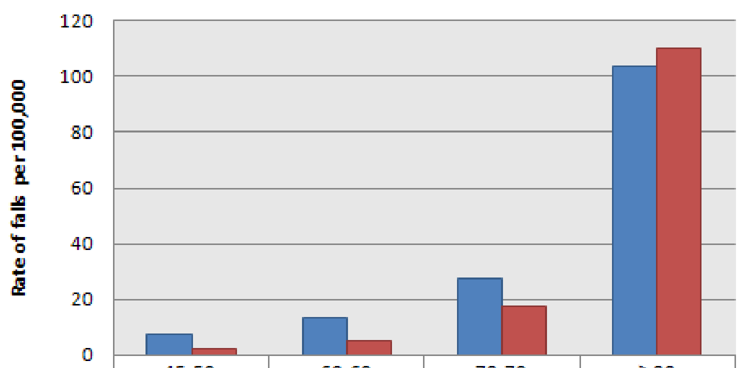
2.3 Factors effecting the probability of falling

With the consideration to reflect 'real life' situations and to model abnormal behaviour i.e. falls among older people, we need to know the incidence rate of fatal and nonfatal injuries among different age groups of older men and women, as well as, the information on the location and time of falls.

2.3.1 Age and sex

Fatal falls

Figure 2.2 shows that the rates of fatal falls increases with age from 9.1 per 100,000 population for people aged 60-69 to 107.8 per 100,000 population for people aged above 80 years. It also illustrates that female rates were constantly lower than male rates, except for ages over 80 years. Male rates were around 3.5 times higher than female rates in the middle-aged group (those aged 45-59 years) [45].



	45-59	60-69	70-79	≥ 80
Men	7.7	13.5	27.3	103.8
Women	2.2	5.1	17.5	110

FIGURE 2.2: World rankings of fall-related deaths by age and sex in 2000 [45].

Non-fatal falls

A United States survey on the incidence rates of non-fatal falls has shown that men are less likely to experience injuries due to falls, as shown in Table 2.2 [5]. Frailty caused by age, reduced or restricted mobility, frequent use of many different medications, and widow status were the contributing factors of non-fatal falls among older women [46].

TABLE 2.2: The occurrence rates of non-fatal falls for older people who lived in the United States, 2001 [5].

Characteristic		Male (n=6,712)	Female (n=15,845)
Age (years)	65-69	1,116	2,022
	70-74	1,249	2,508
	75-79	1,399	2,942
	80-84	1,320	3,174
	85+	1,628	5,199
Injury diagnosis	Fracture	1,946	6,091
	Contusions/abrasions	1,846	4,205
	Laceration	1,272	2,057
	Strain/sprain	580	1,426
	Internal injury	511	957
	Other	549	1,098
	Unknown	8	11
Part of body affected	Head/neck	2,285	4,312
	Lower trunk	1,410	3,821
	Upper trunk	1,034	2,002
	Arm/hand	1,027	2,883
	Leg/foot	860	2,621
	Other	71	159
	Unknown	25	47

2.3.2 Location and time of falls

Based on a cross-sectional research for identifying types of fall injuries in the Netherlands, the number of outdoor falls was reported to be higher than those taking place indoors. More than 55.1% of falls happen outdoors (185 out of 333). The most common place for these outdoor falls is on the street or sidewalk, parks, forests, pastures and playgrounds (44.1%). Meanwhile, the highest proportion of falls inside the house occurred on internal steps (10.8%), followed by falling in the living room (9.3%). The next 5.4% was shared equally by those who fell in the bedroom and the hallway [47]. However, it must be noted that these fractions might be biased by cultural attitudes to lifestyle of a particular country.

Frail people tend to fall inside the home, while outdoor falls are more likely to occur among active persons [48, 49]. Li [50] performed a study in 2001 to find the occurrence rates between fallers (outdoor and indoor falls) and non-fallers. The study population was selected from Kaiser Permanente medical centres located in Northern California. The results of the study revealed that outdoor falls are mostly experienced by people who tend to participate in leisure-time physical activity and indoor falls mostly occurred among people who have poor health and restricted mobility. Other studies also found out that men are most likely to fall outside the house, as shown in Table 2.3 [51]. This may be because men are more engaged in risk-taking activities or are more physically active outside the house.

TABLE 2.3: The occurrence rates between fallers (outdoor and indoor falls) and non-fallers. The study was conducted for two years in the Boston (Massachusetts, U.S.) between September 2005 and December 2007 [51].

Characteristic	Outdoor Faller (n=135)	Indoor Faller (n=129)	Faller(both indoor and outdoor) (n=113)	Non-Fallers (n=318)
Age, mean±SD (years)	79.9±5.5	77.7±4.9	77.9±6.1	77.5±5.2
Men, n (%)	31(23.0)	59(45.7)	41(36.3)	114(35.8)
Women, n (%)	104(77.0)	70(54.3)	72(63.7)	204(64.2)

More than 58.4% of older patients in the Barnes-Jewish Hospital (107 out of 183) tended to fall during the night time (around 7:00 pm to 6:59 am) [52]. Such night time falls occurred more than daytime falls (76/183; 41.53%) [52]. Falls frequently happened during autumn and winter more than in spring and summer [53]. This may have been due to the fact that older people tend to reduce the frequency of outdoor activities during the winter season which could lead to Vitamin D deficiency that may cause reductions of muscle strength and endurance in the lower-limbs [53].

Indoor falls are far more dangerous than outdoor falls, especially when older people are alone at home at night time. This provides us a clear picture that there is a need to develop unobtrusive fall detection systems for application in unsupervised living environments including the home.

2.3.3 Medical conditions

Some research has been conducted to examine the relationship between falls and medications. Fact-finding has shown that frail older people with disease were more likely to experience subsequent falls [54]. These following facts provide some background that can be applied when modeling realistic schedules for healthy and frail older people (with multiple chronic health conditions).

Alzheimer's disease

Alzheimer's disease (AD) has also been implicated as a risk factor for falls. People with the senile dementia form of the Alzheimer's type (SDAT) are three times more likely to fall than those without SDAT disease [55]. Furthermore, a study conducted in Japan by Horikawa and colleagues found that the presence of severe periventricular white matter lesions and the use of neuroleptic (antipsychotic) drugs among patients with Alzheimer's disease can cause postural imbalance which leads to an increased risk of experiencing falls [56]. Moreover, such postural and motor deficits could lead to severe fractures when an AD patient experiences a fall [57], thus causing further difficulty in getting up from the floor without assistance. Since people suffering from AD have difficulty remembering things, it is unlikely they will be wearing a sensor when a falls event occurs.

Depression

In a study by Biderman et al., approximately 47.1% of older people over 75 years of age reporting a fall also reported experiencing symptoms of depression [58]. A later study revealed that significant risk factors for falls included having depression, having an existing injury and using selective serotonin reuptake inhibitors [59]. Depression may cause people not to pay as close attention to their environment as would otherwise be the case [54]. Thus falls in this disease cohort often occur because of uneven steps, sidewalks or wet and slippery floors.

Diabetes

Maurer [60] conducted a prospective study of the relationship between diabetes mellitus and the increased risk of falling at the Hebrew Home for the Aged, which is located in Riverdale, New York. The study revealed that the incidence rates of falls were 78% (14 out of 18 persons) in the group with diabetes mellitus and 30% (35 out of 121 persons) in the group without diabetes mellitus. A cross-sectional study among adults over 60 years reported that women without diabetes mellitus have a fall rate 11.4% lower than women with diabetes. It also reported that women with diabetes mellitus are 1.7 times more likely to be injured by the fall due to decreased balance [61]. Other findings from research in Australia revealed that those people who suffered from diabetic peripheral neuropathy (DPN) have an impaired ability to maintain postural stability when walking on irregular surfaces [62], which may lead to increased falling when walking.

Incontinence

Incontinence is one of the most common chronic conditions afflicting older people. Foley et al. [63] conducted a cross-sectional postal questionnaire study of the association between the increased risk of falls and urinary incontinence. All respondents were randomly selected amongst older people aged 70 years or more living in the UK. A small proportion of these subjects have been found to suffer from mixed urinary incontinence. To investigate the association between pure stress and urge incontinence and falls, some subjects who suffered mixed stress and urge urinary incontinence were excluded. The results indicated that there was a significant positive relationship between pure stress incontinence and falls (P-value 0.007) or pure urge incontinence and falls (P-value < 0.001), as shown in Table 2.4. Also shown for comparison is the association between the risk of falls and the volume of urine lost.

Table 2.4: The incidence of falls related to stress and urge incontinence. It also shows the volume of urine that leaks when a subject experiences incontinence [63].

	No falls in previous year	Falls $\geq$ 1 in previous year	p-value
Complete data for 3,611 subjects	Incontinence not present (n=2,372) Stress incontinence only (n=138)	Incontinence not present (n=1,016) Stress incontinence only (n=85)	<0.007
Complete data for 3,893 subjects	Incontinence not present (n=2,372) Urge incontinence only (n=306)	Incontinence not present (n=1,016) Stress incontinence only (n=199)	<0.001
Amount of urine lost large (made subject soaked/wet)	74	152	<0.0001
Amount of urine lost small (made subject damp/almost dry)	624	485	

The odds of falling for people with urge and mixed urinary incontinence were 1.4 times and two times larger than people with stress incontinence. The study also reported that there was a modest increase in the number of falls for people with urge urinary incontinence [64]. People with urge and mixed urinary incontinence may find an urgent need to go to the toilet followed by leakage that can cause slippery and wet floors. These wet or slippery surfaces as well as the urgent need to find a bathroom contribute to the fall risk.

It is also noted that urinary incontinence can cause older people to go to the bathroom often at night, with the falls occuring on the way to or from the bathroom. However, it is unlikely that subjects will remember to wear a sensor during these night time trips to the bathroom [17].

Parkinson's diseases

Parkinson's disease (PD) is a disease that is characterised by four major features: rest tremor of a limb, bradykinesia, rigidity of the limbs or trunk and postural instability [65, 66]. Some people think of PD as a disease which is usually experienced by older people, but it affects 1 in 20 people aged less than 40 [67].

Due to a difficulty in maintaining balance and controlling their movement, approximately 68.3% of older people with PD reported falling and 50.5% of them had recurrent falls ($\geq$ 2 falls) during a one year follow-up [68]. The increased risk of falling among people who had PD was attributed to the severity of disease, the impairment of balance and depression [68]. A recent cross sectional study involving 160 PD patients, with a mean age of 72 $\pm$ 9.5 years, in Spain estimated that at least 38.8% of patients experienced a fall during the nine month study period; moreover, 24% of these patients experienced frequent falls [69].

People with Parkinson's become less active than they formerly were, their muscle strength tends to wane, which actually increases the falls risk.

2.3.4 Exercise and lifestyle

Some research has been conducted to examine the relationship between falls and lifestyle among older people. Fact-finding and logical reasoning demonstrates that healthy older people are more active around the house. The following facts will give the researcher ideas when modeling realistic schedules which are targeted for active and inactive older people.

Alcohol use

In several studies, it was found that older people with excessive drinking habits have a greater risk of falling [70–72]. Other studies also revealed that many older people especially women prefer to drink at home alone [73, 74].

A study conducted by Lima et al. [70] examined cross-sectional data from a population in Sao Paulo to assess the association between the use of alcohol and increased risk of falling among people aged 60 years and above. The average volume of alcohol consumption, the drinking patterns and the frequency of falls were assessed based on self-reported information by participants. Based on the number of falls reported by participants in the year previous to the interview date, findings showed that older people who reported drinking five or more alcoholic drinks a day had three times higher risk of falling (PR = 3.12; 95%CI: 1.49-6.53).

A case-control study was conducted by Sorock et al. [72] to analyse the causes of death as they related to alcohol in the US. The finding of this study revealed that there was a positive connection between high consumption of alcohol and death caused by falls. They also found that such drinking habits increased the risk of dying by 70%, even after data adjustments for age, gender, history of education and employment in the one year prior to the interview date.

Inadequate diet/exercise

The risk of falls and injuries could be increased by poor diet or inadequate nutrition [75, 76] or not doing regular exercise [77].

Vivanti et al. [76] performed a prospective study to determine the association between malnutrition, the risk of falls and hospital admission. This study targeted older people who attended emergency departments in Queensland, Australia. Patients were categorised as either well nourished, moderately malnourished, or severely malnourished with a subjective global assessment classification technique. The results revealed that 52.6% of older subjects who were malnourished or at risk of malnutrition had fallen during the six months of study (self-reported).

Muscle weakness, diminished physical fitness and exercise

It has been reported that a loss of muscle strength, balance, flexibility and coordination that occurs with aging increases the risk of falls [78].

Morrison et al. [79] targeted older people who suffered diabetes type 2 (62.3±5.5 years) in the intervention group. This group had impairment in balance and decreased reaction time when compared with a control group (64.7±7.1 years). Each participant performed two training sessions, consisting of balance and strength training sessions. The balance training sessions concentrated on components of movement such as lower-limb stretches and leg, abdominal, and lower-back exercises. While the strength training session concentrated on a variety of lower and upper limbs exercises with strength training machines. The intervention group improved in reaction time, leg muscle strength and body sway measures. As a result, these exercises reduced the risk of falls in the intervention group ($F_{1,35}$=33.03; $p<0.05$).

Swanenburg et al. [80] assessed the effectiveness of two interventions: supplementation with calcium and vitamin D and exercise in a sample of 24 older people aged 65 years and over. Participants were randomly assigned to an intervention (n=12) or control group (n=12). Participants in the intervention group attended supervised exercise classes (i.e., muscular strength, endurance, balance, and co-ordination) for three months. The results revealed that the intervention group experienced an increase in muscular strength (analysis of variance (ANOVA F=3.0, p=0.03) and activity level (ANOVA F=3.38, p=0.02) and significant decrease in the risk of falling (ANOVA F=8.90, p=0.008) when compared to a control group. The Berg Balance Scale (BBS) was used to assess the risk of falling. Moreover, the number of falls was reduced by 87.5% in the intervention group by the end of the study.

Voukelatos et al. [81] assessed the effectiveness of Tai Chi interventions on falls and their related injuries. Healthy older people over 60 years of age (n=702) were recruited and randomly selected to an intervention group (n=353) and a control group (n=349). Participants in the intervention group took part in a weekly one hour session of Tai Chi for 16 weeks and were instructed not to practise Tai Chi outside the classroom setting. While participants in the control group stayed on the waiting list for 24 weeks before they started their Tai Chi class. There was no significant difference between the intervention and control groups in the proportion of older people who reported one fall or frequent falls. Tai Chi was more effective in those who experienced three or more falls. The overall fall frequency was reduced in the intervention group as compared to those in the control group. The authors suggested that incorporating Tai Chi into everyday life may become one effective way to prevent falls for healthy older people.

Physical disability

Some chronic physical disabilities that are commonly observed as part of the aging process, for example gait disorders, hearing loss [82], poor balance, dizziness and postural hypotension [83], can increase the risk of falls.

Table 2.5: The associated numbers and percentages of falls that occurred during the implementation of study [82].

Parameter	n	%
Fall occurrence (n=423)		
At least one fall	199	47.0
At least two falls	92	21.7
At least one injurious fall	121	28.6
Unknown	11	2.7

The association between hearing loss, postural balance and falls was investigated on 103 monozygotic and 114 dizygotic female twin pairs aged between 63 and 76 years. The centre of pressure (COP) movement during semitandem stance with eyes open and closed on a flat surface was used to evaluate postural balance. Falls were recorded by self report using a falls calendar daily. The data shown in Table 2.5 revealed that the combination of severe hearing loss, severe postural control deficits and old age resulted in a higher risk for falls [82].

Risk-taking behaviours

Older people who do not realise that their physical abilities are declining often attempt to perform activities that can cause them to fall. It is fairly self-evident that they should avoid activities that put them at risk of falling (i.e. walking without a mobility aid when needed, inappropriate use of a mobility aid, clearing snow and ice off a walkway, climbing onto ladder or chair or unsteady stool to reach objects or clean surfaces) [84].

2.4 Video surveillance for fall detection

Video-based approaches are being used in home-based assistive systems because they provide advantages over other types of sensor approaches and the cost of video-based systems is falling [85]. One of the advantages of using a camera sensor is the ability to detect multiple events occurring simultaneously. Furthermore, this approach does not require any device to be attached to the subject.

In the literature, the video-based approaches generally use three common techniques for detecting falls: inactivity detection, (body) shape change analysis, and 3D head motion analysis [86]. Inactivity detection uses the principle that falls can cause fainting or lying down inactively on the floor [86]. Body shape change detection algorithms use the principle that falls can be inferred through sudden changes in posture [86]. In the analysis of the motion of 3D head models, falls from walking can be inferred through a change in vertical and horizontal velocity of the head [86].

The systems which use one camera could fail to recognise a fall occurrence in the case of occlusion [87]. These occlusions frequently happen in real environments because of the existence of furniture in a room and relative locations of subject and camera [87]. This limitation could be solved by using multiple cameras that capture the same subject from different positions. As a result, it becomes possible to extract human body silhouettes in three-dimensional (3D) space [87].

2.4.1 Currently available systems

Use of one camera

Doulamis et al. [88] used a video camera for distinguishing falls from normal events. There are two steps involved in the proposed algorithm. The first step is to separate the foreground objects from the background. Next, the trajectories of the moving object are analysed to determine the occurrence of falls. The overall sensitivity and specificity of the system were 76.46% and 88.4%, respectively. However, although the implementation is in real time, this approach requires a relatively high computational load thus preventing implementation on a large scale, at reasonable cost [89].

Nait-Charif and McKenna [90] utilised a wide angle, ceiling-mounted camera, in their system. The system infers the occurrence of falls when a subject is motionless outside the normal inactive areas (such as a sofa or couch whereby people are often relatively motionless, as they may be sleeping or watching TV). The results showed that the algorithm achieved an accuracy of 96.9%, but the pilot study involved only one young healthy volunteer in a small room.

Rougier et al. [91–93] traced the head movement position using particle filters to calculate the head pose, and discriminate falls from normal situations from the head trajectory. The system achieved a sensitivity of 88% with specificity of 87.5% when distinguishing falls. However, the obvious disadvantage of their method was the requirement to manually bootstrap the system by indicating the head position.

Villacorta et al. [94] used a combination of audio and visual sensors to detect falls in two different settings (nursing home and one bedroom house). The proposed system will generate alarms if the vibration pattern represented the sound of the falling body and the video showed images of people lying down on the floor. However, this work comprised an intrusive approach since they used a video surveillance system along with audio analysis to confirm that a fall event had occurred. No performance data were reported in their publication.

Using multiple cameras

Cucchiara et al. [95] made use of a calibrated camera to obtain body shape and recognise fall events. In dangerous situations, an alarm could be activated by sending a short message service (SMS) message. In the end, the received alarm validation process checks live video streams as a "second opinion" by operators/remote users. Bandwidth usage optimisation involves semantic and event-based transcoding algorithms. The multi-camera posture classifier was able to quite successfully recognise human posture, even though the body shape was incomplete, by keeping temporal information from another camera (where the track was not occluded). No trialing of system performance was reported by the authors.

Jansen and Deklerck [97, 98] used a three dimensional (3D) tracking solution to extract a set of features including the distance between head and floor, the orientation of the body and the period of inactivity to identify whether falls had occurred. One limitation of this research is the necessity to install multiple calibrated cameras within the home environment.

Pham et al. [99] placed a multi-camera system in the room to distinguish an emergency situation such as falls from daily life. Firstly, the system extracted the human silhouette from the background. Next, the system evaluated the moving object trajectories to determine whether a fall event had occurred. As for Jansen and Deklerck

[97, 98] as well as Cucchiara et al. [95], no mention was made as to how well the systems performed in any form of testing or trials.

Williams et al. [100] proposed a system that can track the location of an individual and detect falls when they are present. First, the human silhouette is extracted from the background by using a simple background subtraction technique and then the body width-height ratio is used to discriminate falls from daily activities. The system assumes that the person has fallen if the ratio is above a pre-determined threshold value. The accuracy of the system was above 94%. But, this study only involved a small number of healthy participants (4 subjects).

Zambanini et al. [101] placed four cameras in the corner of a room and investigated two different approaches for falls detection. In the fist approach (early fusion), a fall algorithm was implemented using a 3D human voxel volume representation. The reconstruction process was performed based on the combination of multiple video camera views. In the second approach (late fusion), a fall algorithm was implemented for each camera and fuzzy logic was used to combine the results. The results showed that the early fusion approach (sensitivity of 97.7% and specificity of 86.7%) was

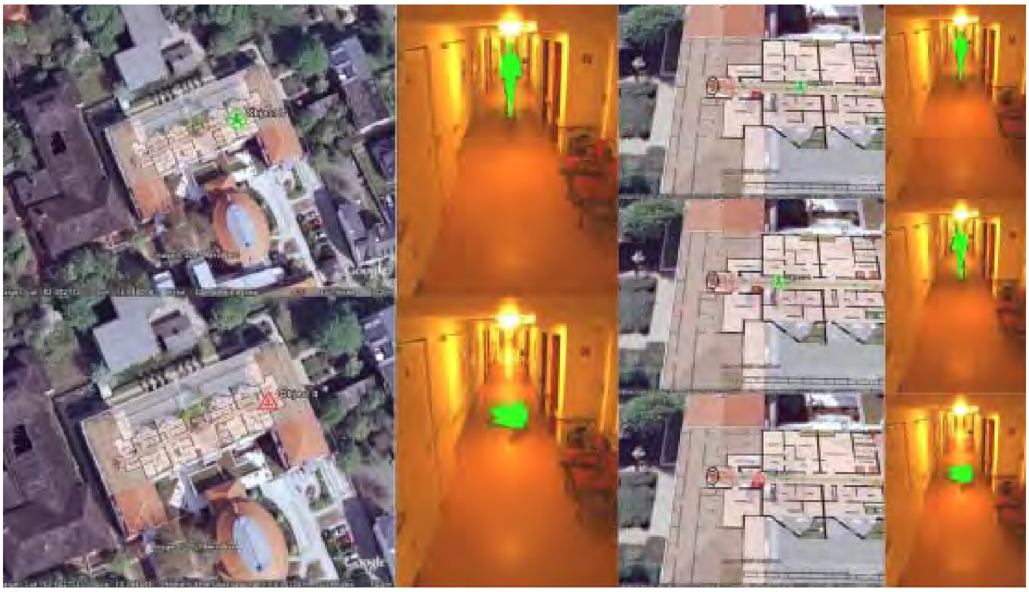


FIGURE 2.3: A floor plan of older care people was displayed using Google Earth. As shown in the figure above, one person experienced falls inside an elder care facility. The authors used multiple cameras for monitoring the person's movements in real-time and recognising falls from ADLs. This was followed by marking the location of the fallen person in world coordinates [96].

much better to recognise falls than the late fusion approach (sensitivity of 83.7% and specificity of 76.7%). Even though the results are quite promising, it should be noted that this research as with other research which is based on video analysis is hindered by privacy concerns which can affect the acceptance of this system.

All of the above studies can be quite expensive and are far more intrusive than other approaches since multiple video cameras are installed to cover the entire room [102].

2.4.2 Discussion

The following disadvantages when using video analysis to detect falls are: increased concerns over invasion of privacy [103], high computational complexity and relatively high sensor power consumption [104].

Privacy

The results from one questionnaire showed that 78% out of 23 older people would not accept a video surveillance since it captures everything that occurs in the house and violates their privacy [105]. In contrast, results from the research conducted by Steele et al. revealed that the majority of participants are more concerned about their safety rather than their privacy. But it was also noted that one of the 13 participants did not tolerate any camera video for continuous monitoring [106].

False alarms

Inactivity detection algorithms produce late alerts because they only identify falls when the older people is already lying down on the floor. These techniques are also liable to false-alarms even if they use the context information to support decision-making. Shape change analysis algorithms only consider a small number of features, generally only determining the width or height ratio of an image of a body-shape. It does not detect the stages of falls. Moreover, the process of tracking the position and orientation of a head in three dimensions using a single omnidirectional camera is unreliable and very slow/computationally expensive.

2.5 Wearable sensor based fall detection systems

Since video analysis-based approaches still suffer from increased concerns over invasion of privacy [103], some current research has evolved in the direction of using wearable sensor-based solutions to detect falls. The wearable sensor device approach can be defined as holding or wearing embedded sensor devices with the intention to identify daily activities and fall events.

2.5.1 What is an ideal system?

The form factor (weight and dimensions of the sensor) is the key design factor of wearable devices [107–109]. The results from questionnaires showed that 82% of 23 people people did not mind to use tags on clothes [105]. It is also interesting to observe that older people would love to see representation of the device in the form of either a watch or a ring [106].

Device packaging must have little or no adverse or harmful effects. Rubber and metal can cause an allergic reaction which can include itching, burning and red skin rashes. This means that the wearable device mast be made from allergy free material [105]. Also, such devices must be water and heat resistant so that the end user does not need to remove the device while they are showering [105]. This is important because according to a prospective study of inpatients falls, 20 out of 183 people experienced falls in the bathroom [52].

Moreover, the system must also be able to differentiate falls from different directions (forward, lateral and backward), different speeds (fast and slow) and in different environments (living room, bedroom, kitchen and outdoor garden). Therefore, the ideal performance of the system should allow early detection of falls for immediate medical attention to help avoid severe injury.

2.5.2 Currently available systems

Positioned into a hearing aid

Lindemann et al. [110] positioned two triaxial accelerometers orthogonally into an ear-level hearing aid housing. There were three threshold requirements to distinguish falls: the acceleration sum vector in the xy plane (x-axis = frontal, y-axis = sagittal) greater than 2g; the velocity sum vector for all spatial components just before the impact exceeding 0.7 m/s; the acceleration sum vector for all spatial components above 6g. Although, results showed a sensitivity of 100%, but the system was only tested on one young subject and one low falls risk older woman. Moreover, the placement of the sensor would become an issue when considering both ergonomics and battery life.

Worn as a smart garment

Lin et al. [111] made a micro-sensor system inserted into a coat to obtain the body orientation changes during an impact. A total of ten micro-sensors (a micro mercury switch and an optical sensor) were placed in different parts of the coat. The data analysis was performed using an embedded microprocessor to detect various body positions. The sensitivity of the system varied between 98% and 100%. The results are hard to interpret since the author did not specify the number of people participating in the study.

Nyan et al. [112] developed a wearable garment containing a triaxial microelectromechanical system (MEMS) accelerometer positioned at the shoulder. The data analysis was performed to discriminate falls from ADL. The specificity and sensitivity of the system were 98.8% and 95%, respectively. While the results were promising, this study only recruited a relatively small group of healthy volunteers (3 males and 3 females). Even though the system performed well during all tests, it is likely that battery life would be short since the sensor is continuously transmitting acceleration signals using a Bluetooth^{TM} transmitter to processing module.

However, it should be noted that the approaches above are faced with several challenges that need to be addressed. In consideration of cost, this smart garment must be washable or be able to be used frequently without breaking the existing sensors.

From a practical view, forcing subjects to wear a cloth with the sensors placed at fixed positions would raise many compliance issues.

Embedded into a wrist watch

Degen et al. and Estudillo et al. both embedded accelerometers into watches to detect falls with the consideration that such a device would be small and more comfortable for use by older people since most older people do not want to be seen as frail [106].

Degen et al. [44] recruited three healthy subjects in their study. Simulated forward, backward and sideways falls onto a mattress were tested.The system successfully recognised 100% of the simulated forward falls, 58% of the simulated backward falls and 45% of the simulated sideways falls. The difficulty of detecting sideways falls was raised because of a short distance from device to ground. Also problems in detecting backward falls occurred because the subject's arms are oriented towards the opposite direction to the fall. After the laboratory trial, the subjects continued to wear the device for 48 hours while performing their daily activities, with the intention to test the occurrence of false positives. The results showed that the device worked well due to no false positives being detected.

Estudillo et al. [113] created a watch which included an accelerometer, a processor and a wireless transmitter. The algorithm divided each of the accelerometer data streams into 90-sample segments and used both temporal and frequency analyses to detect falls. The temporal analysis of postures was performed by calculating the changes of angles in the vertical direction of acceleration. The frequency analysis was performed to differentiate between fall impacts and non-fall impacts. The algorithm was validated using 332 activity samples from 31 healthy and young subjects. While the accuracy rate was nearly perfect, the methodology only involved limited testing on healthy volunteers. Moreover, the battery only lasted for about 14 hours.

Created a wearable airbag

In a very different approach, Tamura et al. [114] created a wearable airbag that consisted of a triaxial accelerometer and a triaxial gyroscope placed on the neck and the hip. An array of fall scenarios were tested, either forward, lateral or backward. Free falls were determined when accelerations went outside a range of $\pm$ 3m/s and the angular velocity exceeded 30 degree/s. The system was intended for reducing impact on the human body by inflating the air bag when a fall occurred, before the person impacts the ground. The algorithm still needed to be improved to distinguish jumping and running from actual falls. Moreover, there are obvious compliance issues with using an airbag, which is a large protection device, in everyday activities.

Placed into an enclosure

There are four common locations that are used for the long-term monitoring: on the wrist, the chest, the shoulder and the neck [115].

A commercial wearable sensor called Mobile Personal Emergency Response System (M-PERS), is a device that contains a triaxial MEMS accelerometer to distinguish falls from other normal activities (Figure 2.4). The device is small, and can be clipped to clothes or placed in a pocket. It also works outside the house when paired with Wellcore compatible cell phones. When a fall has been detected, the system is able to track cell phone location via the GPS satellite network and send immediate help (information comes from website: http://www.wellcore.com/). Moreover, the device is waterproof so it can still be used even on rainy days.

FIGURE 2.4: Wellcore launched a commercial product called Mobile Personal Emergency Response System (M-PERS) for detecting falls. Part of the figure comes from website: http://www.wellcore.com/.

Hasen et al. [116] created a sensor-based system to detect falls. The device consisted of accelerometers and a processor to provide real time analysis and motion event classification. The trial study involved only three older persons that performed their daily routines. The system is still under development and is being used for collecting motion and image data at a local elder care facility.

Five volunteers performed a set of simulated fall movements in order to test the sensitivity of a system that was made by Huang et al. [117]. The device consisted of an accelerometer mounted at the head. The location of falls could be tracked based on a received signal strength indicator measurement. Although the system's performance was found to be perfect (the associated sensitivity and specificity of system were 100%). As mentioned earlier, the study only recruited five young people. The detection of posture change with a head worn accelerometer is a partial problem since the head is not aligned with the torso if the subject lifts their head while lying. Also, the placement of an accelerometer on the head level requires a detailed hardware design to gain user acceptance.

Kangas et al. [118] patented a device for detecting falls and monitoring the health status of the elderly. The extraction of signal information and the interpretation method to classify accelerations and body position during fall events were included in the fall monitoring system. The health monitoring status provided automatic notification when assistance was needed by the subject. A series of three laboratory experiments were conducted to find the optimal attachment position for the accelerometer, to form the fall detection algorithm and to define the accuracy of the system. Then, a series of data collected from the field were used to verify the fall detection system. In total, this study included 25 middle-aged and 37 older people. The sensitivity of the system to distinguish simulated falls from ADL was 97%, which decreased to 72% for actual falls. This decreased sensitivity may be associated with the fact that high pre-impact velocities were not detected when older people fell out of bed.

Li et al. [119] presented a fall detection system that consisted of a triaxial accelerometer and a triaxial gyroscope. These devices were placed on the trunk and upper leg. Three young males performed three different simulated falls movements: fall-like motions (quickly sit-down upright, quickly sit-down reclined), flat surface falls (forward, backward, and sideways falls) and inclined falls (falls on stairs), along with a series of daily activities. The activity intensity was analysed by calculating acceleration amplitude and rotational rate. The posture was recognised by measuring inclination angles of the trunk and thigh. The transition was analysed by comparing acceleration and angular rate changes with predetermined thresholds. Although the associated sensitivity and specificity were higher than 90%, the algorithm failed to detect falls if the subject landed in a sitting position on the floor after the fall.

Mathie et al. [120] utilised a similar methodology for fall detection using triaxial accelerometry. Various parameters (such as the angle of tilt, time duration for maintaining posture, energy expenditure (metabolism), and the previous and next activity) were used in this research. The effects of three parameters were investigated: the smoothing median filter length, the averaging window width, and the threshold value for the acceleration magnitude. One important factor was in choosing the latency time to be long enough to reduce the number of false positives. The methods developed in this research showed an accuracy of. 95.6% in subsequent research by Karantonis et al. [121] for a real time falls detector, also from the same laboratory at UNSW as Mathie. The study's drawback was very limited numbers with healthy people (five subject with age between 22 to 23 years and one person aged 60 years).

A wearable wireless body sensor device was developed by Li et al. [122] to recognise the subject's activity with the intention of detecting falls, using both accelerometers and gyroscopes. Four different techniques were used to analyse and to detect falls: orientation change algorithm (OCA), acceleration based algorithm (ABA), hybridisation (an algorithm which is a combination of OCA method and ABA method), and a SVM classifier. Among all four methods, SVM, has the highest accuracy of 95% when distinguishing falls from ADL. However, the sample size was too small (three males and one female) to give reliable results.

Weiss et al. [123] proposed a solution to detect near falls automatically. In this study, each subject walked for two minutes on a treadmill either with or without obstacles at three different paces (slow, normal and fast). Findings from the research revealed that the accelerometer can be used for recognising near falls by finding four different types of derivatives (anterior posterior derivative, vertical derivative, medio-lateral derivative, vertical maximum peak-to-peak derivative) and by calculating the signal vector magnitude and vertical maximum acceleration. It was found that the best parameter to identify a stumble or near fall was the vertical maxp2pdiff with a sensitivity of 85.7% and a specificity of 88%. The remaining question needed to be addressed is whether this method will works outside of the lab when people are not just walking.

Other studies used triaxial accelerometers that were placed on different areas of the body, such as at the waist area, developed by Al-ani et al. In this case, while the recognition rate for falls was above 99%, their subject sample size was far too small (only two subjects) to reliably distinguish falls from ADLs [124]. Further studies by Torrent et al. [125] placed devices on the chest area in combination with a triaxial gyroscope and a temperature sensor (the authors did not publish the detection accuracy rates).

In all the above studies, fall simulations were conducted onto protective layers of mattresses which can change the characteristics of fall impacts and thus does not represent actual falls in older subjects [126]. In actual falls, many older people hit the ground harder with impacts higher than the average impact force in simulated falls [126]. Conversely, some older people gradually collapse onto the ground, by sliding down a wall for example. These real fall profiles are rarely captured accurately by healthy, younger subjects.

Created a tag

Bowen et al. [127] placed radio-frequency identification (RFID) tags into wristbands in order to identify a wearer's orientation. In the first stage, a mannequin was used in the test to prove the feasibility of the use of a real-time locating system (RTLS) wristband to identify three different types of falls (falls from standing, falls while sitting on a wheelchair and falls while lying down on a bed). In the second stage, one female subject repeated the experiment by performing those same falls onto protective floor mats. The system performed quite well in detecting falls (an accuracy of 89% and 80% for tests which involved a mannequin and a single human subject). Since this study only involved one person, it would be important to expand this research to include more volunteers from different ages to increase the robustness of the system.

Lustrek et al. [128] placed RFID tags on the chest, wrist and both ankles. The datasets from those sensors (consisting of the tag velocities and the distances between tags) were used to train machine-learning classifiers for the purpose of recognising falls. Findings revealed that the placement of tags on different parts of the body could improve the performance of the falls detection algorithm with an accuracy of 94.7%. However as previously noted, this solution may not be practical because older people are often unwilling or may forget to wear such sensors.

Embedded into a shoe

Gupta et al. [129] developed a monitoring detection device by placing a wearable device on the wrist and embedding sensors (one triaxial accelerometer and four pressure sensors) into a shoe insole. The data from both wearable sensors were transmitted to a local server for further analysis. The results revealed that the system was quite successful in distinguishing falls on a flat area with a sensitivity of 95% and specificity of 100%, but failed to recognise falls on stairs. Moreover, the wearable devices have poor battery life, since the data must be transmitted continuously to a server for further processing and analysis.

Embedded into a mobile phone

Some researchers considered the use of mobile phones as a tool for the detection of falls [116, 130–134].

Dai et al. [130] embedded an accelerometer into the Android G1 phone and performed extensive experiments that involved 15 young subjects. The mobile phone was placed in three different locations: in the pocket (chest), on the belt (waist) and in the pocket of the pants (thigh). Each subject performed a series of predefined simulated movements: 1. Simulated falls with different directions (forward, lateral and backward), different speeds (fast and slow) and in different environments (living room, bedroom, kitchen and outdoor garden); 2. Simulated ADLs including walking, jogging, standing and sitting. The range of false negative rates for forward falls, lateral falls and backward falls were 1%-3.1%, 2.2%-10% and 1.1%-5%, respectively. Even though the battery lasted for 34 hours it would still cause inconvenience for users since they would need to recharge the device every couple of days.

Sposaro et al. [131] embedded a triaxial accelerometer into a mobile phone. Falls events were detected when the amplitude crossed either an upper or lower threshold within a certain time window along with a change in device orientation from the vertical to the horizontal. The device also incorporated a global positioning system (GPS) and two-way radio to summon help when an emergency situation occurred. This approach is reasonable since many people will have a mobile phone. The results showed that making and answering phone calls can cause a false alert.

Zhang et al. [132] also proposed the use of triaxial accelerometers in a mobile phone to detect falls. The system has been tested on various types of movements, including ordinary activities of daily living performed by twelve older people (aged 60-80 years), and high-intensity activities of daily living and simulated falls performed by twenty younger people. The mobile phone was placed in a cloth pocket or hung on the subject's neck. An SVM classifier was first used to extract features from motion signals. Then, a combination of Kernel Fisher Discriminant and k-Nearest Neighbour algorithm was used for classification of fall events. The accuracy rate was 97.5% and 96.6% for identifying low and high risks of falling. However the problem with mobile phones is that the system can only work if the user does not forget to carry their mobile phone. A similarly issue arises when the phone needs to be routinely recharged.

Embedded into a walking stick

Almeida et al. [135] incorporated a sensor into a walking stick to detect falls and to measure the walking speed. The device utilises a single gyroscope to estimate the velocity of the stick away from the vertical. When the movement away from stick's stable point is equal to or above the maximum angle from vertical, it can be inferred that the subject might have experienced a fall. The authors also developed a new method for calculating the average human walking speed. However, this device has only been tested with simple movements such as walking at different paces instead of falls.

Lan et al. [136] used a walking stick with the ability to differentiate between various types of falls and daily activities. The authors argued that this solution is best suited for unobtrusive monitoring since a walking stick is commonly used to help older people maintain their balance while walking. The device contained a contact pressure sensor, a triaxial accelerometer and three single-axis gyroscopes. The alert is raised if three stages of falls have been identified: a rapid change from vertical to horizontal position, the detection of a ground impact and the stick lying flat on the floor. These stages are needed to decrease the number of false positives, for example, when a subject accidentally drops the stick. The accuracy of the system is nearly perfect (99.17%) for detecting different types of falls (forward fall, backward fall, sideward fall and free fall). However, there is an obvious limitation to implementing this solution: the fact that the user may not always be using their stick.

2.5.3 Discussion

Cost

An affordable system is another issue that should be addressed [106]. The cost for the device and ongoing maintenance must be reasonable when compared to any expenses that may need to be paid to treat a resultant injury associated with a fall [106]. In broad terms, nowadays the price of such devices is reasonably cheap [137].

Form Factor

The sensor's visibility and design also influences the willingness to use a wearable device because users may be afraid of being labeled as dependent on others [138]. Today, the size of wearable sensors however is steadily becoming smaller [111]. In the future, the major improvements in wearable sensor technology will be achieved by making miniature devices or reducing the requirement of maintenance action. The current expectation of form factor is nearly the size of a "box of matches" (15-20 mm^3) and a weight that is less than or equal to a watch (20-30 g) [139].

Portability

Falls are also not confined to just inside the house. A wearable sensor gives a distinct advantages since it can continuously monitor activities either inside or outside the house [105], making them highly attractive to many researchers [137].

Sensor lifetime

Many older people are worried that a fall may occur during the time when a sensor is dysfunctional due to a flat battery [106]. Maurer et al. [140] created an eWatch that could be used as a single device for multiple purposes such as activity monitoring and as a fall detection system, general interface for smart environments, and context-aware notifications. The lifetime of this device was around 56 hours. Another fall detector inserted into a wrist watch was developed at the Swiss Center for Electronics and Microtechnology [141] and the battery of the watch provided up to 15 days or 1 month of battery life, depending on the sampling frequency and the detailed requirements for data handling. It has been argued that the battery life time should reach at least one-year [139] to prevent this condition from occuring and to lower maintenance and associated costs.

Emergency alert

Most people (87% out of 23 older people) agree that in the case of emergency, the wearable sensors must be capable of providing an alert signal that links directly to an emergency call centre [105]. They also noted that the call centre staff can then try to contact the person or family member. If neither of these can be contacted or if the person is in need of medical care, an appropriate emergency service would be notified.

Table 2.6: The occurrence rates of falls-related alarm activations for seniors. Most of the non-alarm users were alone at the time when falls occurred (64 out of 144 older people) and could not get up from the floor by themselves [142].

		Alarm Users, (n=124) (n(%)	Matched sample of non-alarm users (by age, date and type of ambulance service, (n=144) n(%)
Gender	Female	89(72%)	84(58%)*
Fall location	Home	121(98%)	100(70%)*
	Residential care facility	1(1%)	32(22%)
	Public place	0(0%)	12(8%)
	Not recorded	2(1%)	0(0%)
Alone at time of fall	Yes	97(78%)	64(44%)
	No	27(22%)	79(55%)
	Unknown	0(0%)	1(1%)
Ambulance called by	Self	115(93%)	21(15%)
	Family	5(4%)	66(46%)
	Health care staff/carers	2(1.5%)	41(28%)
	Other	2(1.5%)	16(11%)

*significant difference between alarm and non alarm users $p<0.001$

A retrospective study based on data collected from the South Australian Ambulance Service revealed that the typical response time for acceptable medical care would be between 5 and 15 minutes, after calling the ambulance service [142]. The result also revealed that most subjects are alone when falls occur as listed in Table 2.6. These findings show that it's important to have a system that will detect fall events and track the location of the subject.

The device function can be enhanced by embedding real-time automatic fall detection features and sending an alert via a cellular telephone to the formal caregiver and family member [143, 144].

Comfort and convenience

The feeling of comfort and convenience has to be counted as the major reason for using and accepting devices [145]. The user acceptance for wearable devices is lower [146] since it needs to be worn 24 hours a day to ensure gap-free monitoring. Algase et al. [147] demonstrated that people with dementia often do not wear body-worn sensor devices in their daily living. In terms of functionality and convenience, the push button on the wearable sensor could be useful to call emergency services directly in the event of an accident.

Performance

A wearable fall detection system alone has yielded an accuracy ranging between 93% and 98% [13, 148]. Thirty people used a prototype that was created by Lee et al. [148] for monitoring activities. In the final stage of design, experimental results obtained with 360 different fall scenarios showed reliable detection performance (93.2%). Mathie et al. [149] proposed sets of simulated events involving sit-to-stand and stand-to-sit transitions and walking that were tested in 26 healthy subjects. The results of the analysis between activity and rest illustrates that the associated sensitivity and specificity of the system were higher than 98% and from 88% to 94%, respectively. Eight young male subjects used a prototype wearable device that was created by Ojentola et al. [150] for differentiating falls from normal activities. The accuracy is quite high for detecting normal events (precision, 81% and sensitivity, 92%). Listed results are not necessarily likely to apply to an older cohort, the rates could be lower in the real environment due to some older people feeling embarrassed or ashamed about wearing the fall detector and tending to forget to use it because of aging and disease.

2.6 Ambient sensor based fall detection system

Current research shows that wearable sensors can be used to reactively identify falls from ADLs [13, 14] and to track moving individuals around the house [15, 16]. Since this solution in general suffers from user non-compliance issues, caused by a number of factors: the device being uncomfortable to wear, being viewed as a stigmatising symbol of their age and physical frailty, or simply due to forgetfulness (with the latter a considerable problem for those suffering cognitive impairment due to dementia-related disorders [17]), alternate approaches based around instrumenting a person's environment have been explored. The ambient device approach can be defined as the action of installing multiple field sensors to assess data related to activities in the environment.

2.6.1 Currently available systems

Use of pressure sensors

Gaddam et al. [151] developed a bed occupancy sensor which was placed underneath the mattress of older people to monitor the use of the bed. The system collected and stored historical data, which was then used to compare with the current bed usage data. The system may assume that a fall has happened when an elder is alone and not in their bed in the middle of the night for longer than a certain threshold time-interval. In this situation, the system would trigger an alarm and contact family members or a GP for first aid and emergency medical services.

Srinivasan et al. [152] developed a prototype floor sensor with several sensor mats capable of gathering real time data on the location and amount of applied pressure. The preliminary results revealed that the system could track foot steps and the applied pressure in real time. This prototype can be used as an alternative solution to detect in a precise way if a person is lying on the floor. However, this approach is quite expensive since there is a need to cover the entire area with pressure sensors for precise detection.

Use of sound sensors

Alwan et al. [17] used vibrations on the floor to detect falls. The system only generated fall alerts when the pattern of vibration was similar to the pattern of vibration generated when a human body falls to the ground. Subsequently, a fall alert was sent to family members or carers of patients by means of the telecommunication network. However, the research also revealed that placing the fall detector on a shared wall between two apartments could cause misclassification errors since the system may detect a fall occurring in a neighbouring apartment.

Zhuang et al. [153] conducted research with the aims of classifying and detecting fall sounds in the presence of noise. Participants were asked to perform day-to-day activities and simulated falls. Then, the datasets were split into training data and validation data. The falls detection accuracy of a model based around a Gaussian Mixture Model (GMM) was 64%.

Used of multiple ambient sensors

Knight et al. developed a system using a combination of capacitive proximity sensor arrays and pressure sensors to recognise a situation where a person tries to get up from a wheelchair and suffers a slip or fall [154]. The system assumes that the person has risen from the wheelchair - if there is a sudden increase in the amount of pressure applied to the seat before the person rises. As soon as the subject attempts to leave the wheelchair, the system activates an early warning message to persuade the person to stay seated in the chair or to summon a nurse using the call bell. A limitation of the system is that it only monitors a person who falls from a chair (or wheelchair). Furthermore, feedback which discourages mobility is perhaps not appropriate for the normal home setting.

Toreyin et al. [155, 156] used a Hidden Markov Model (HMM) based algorithm to detect falls by fusing movement and sound data. The HMM was used for human motion modeling and to distinguish the difference between falling sounds and other sounds in the environment. The algorithm incorrectly recognised 7 of 16 walking events as fall events when using audio data only. It needed a combination of audio and motion sensor data in order to correctly identify the entire walking events.

Zhang et al. [157] developed an unobtrusive falls detection system intended for night time monitoring. The system comprised PIR and PM sensors. The PM acted as a switch, generating a binary signal when pressure was applied [158]. The PM sensor could monitor changes in force, within a certain range of pressures (about 2-30 psi) and up to a certain area (about 0.21 m^2). The PIR sensor (MP Motion Sensor NaPiOn, Panasonic Electric Works Co., Ltd.) measures changes in infrared energy levels; in particular energy radiated by the human body. The system had a lower sensitivity rate of 59.6% when detecting three different types of falls (fall with recovery, falls with and without lose of unconsciousness). Moreover, the system was limited to only monitoring one person during the night time.

2.6.2 Discussion

Ambient sensors offers obvious advantages for falls detection and activity monitoring when comparing with other more intrusive modalities such as video analysis [86]. One of the main advantages when comparing ambient sensors to wearable sensors is that ambient sensor approach makes no assumptions about subject compliance and adherence in terms of attaching and wearing a device [159].

However, the above studies still do not address a number of major issues. Firstly, the developed algorithm assumes that the subject is always inside the house; however, leaving the home without deactivating the system would cause the algorithm to infer that an abnormal or dangerous event had occurred, such as falls with loss of consciousness, due to the subsequent inactivation of sensor nodes. Secondly, the algorithm assumes that there is only one person present in the home, hence precluding its use in aged care or nursing home facilities since it may have difficulty in differentiating which motion belongs to which person for the case of multiple persons in a specific area [160]. Thirdly, it is very hard to differentiate whether the pressure derived from such sensors as pressure mats is from the weight of a human or an animal, as a result, this approach tends to have a high rate of false alarm [161]. Finally, and most importantly, if a subject experiences a long lie and is moving on the floor then the system would not distinguish the fall from an ADL, as the sensors would be continually activated by the person's movement on the floor.

2.7 Smart home

The aging population means an increasing number of elders will be at risk of experiencing debilitating health problems such as hearing loss, memory problems, cataracts and rheumatism. Visual interaction is useless for elders who have visual impairment. An elder with hearing impairment cannot use a system that incorporates voice control or auditory alerts. Considering this fact, the researcher should endeavour to design the system in as simple a way as possible [105].

The presence of telecare or telehealth monitoring among older people living in their own homes can lead to a higher level of independence [105]. As a result, it can help seniors maintain their freedom in their own home and prevent them being admitted to nursing homes or assisted living facilities.

2.7.1 What is an ideal system?

The bigger the house, the more ambient sensors likely to be needed, and subsequently the higher the projected cost. To decrease the cost, the coverage area of the sensor must ideally be large enough to cover the entire room, regardless of size. A variability in house construction materials must not affect the performance of the system [22].

The layout of rooms can be varied from one time to another since many people like to rearrange their furniture when they want a new change of environment. These situations could affect the performance of the sensor since infrared radiation from warm objects (i.e. a human) gets blocked by furniture and/or decorations. Moreover, the power consumption must be low since ambient sensors may need to communicate with a local server wirelessly [22].

2.7.2 Currently available systems

Several examples of smart homes equipped with multiple sensors are the intelligent dormitory (iDorm) [162] and the Place Lab [163].

Akhlaghinia et al. [160] investigated the potential usefulness of an unobtrusive system, based on the use of passive infrared sensors (PIRs), door contacts sensors and Zigbee tags to automatically recognise daily activity sequences in the home environment. The data collection was performed in a flat in Nottingham, UK, which was inhabited by one older woman. During the data collection process, the subject was doing her usual routine, moving with the use of a walker as an assistance device. Some visitors (i.e., a maid service and a nurse) also visited during the day to help her with daily tasks. The aim of this research was to build a system that monitored the activities of one person, however, the existence of other people in the house could activate PIR sensors in different rooms. One way to solve this problem was to eliminate unnecessary signals which were triggered by other visitors. The appearance of the visitors could be recognised by placing a door contact at the entry door to the house. This filtering process began by deciding whether the subject was alone in the flat or other people were with her in the flat. If the subject was alone then monitoring activities could be conducted using PIR activity. But if she was not alone, the activity monitoring was performed by tracking the location of her walker based on received signal strength indicator (RSSI). RSSI can be defined as the measurement of strength present in a received radio signal, usually in the units of dBm. It is calculated from ten times the logarithm of the ratio of the power at the receiver end to the reference power [164].

Cook et al. [165] developed a smart home that consisted of different types of sensors such as motion sensors, temperature sensors, sensors for monitoring hot water supply, cold/recirculation water supply and the use of stove and switch sensors attached to the body of electric appliances, a medication container and jars of dry ingredients. They recruited 20 undergraduate students to perform five different activities such as using a telephone, washing, preparing meals, cleaning the house, eating and taking a pill. They also recruited two undergraduate students to stay in the house for eight weeks for understanding the complexity of human behaviour. A total of 208 datasets were collected for algorithm development purposes. This research illustrated the possibility of experimenting with new technology in real life situations by incorporating ambient sensors.

Helal et al. [167] developed a smart house for assisting the elderly so that they can live actively in their own house and achieve a better quality of life. The whole-house is equipped with (a) several cameras located in the porch and patio, that operate by detecting movement within their field of view and also process images for security purposes; (b) smart blinds that can be configured and reprogrammed to control the amount of sunlight that comes into the house; (c) a number of ultrasonic sensors that are attached to every corner of each room for detecting movement, orientation and other changes in the room which would inform the latest location of the resident; (d) a smart floor fitted with pressure sensors for detecting a fall and generating an emergency call; (e). smart displays for delivering information and entertainment that can follow the movements of the resident from room to room within the house. The smart house supports many other additional features, including a smart mailbox for notifying a resident when a letter has arrived, a smart front door that recognises when someone enters or leaves the house, a smart bed for monitoring and evaluating residents during their sleep, a smart bathroom that includes sensors for monitoring the resident's daily toilet paper and liquid soap usage, for regulating the water temperature in the shower and for reminding them to flush the toilet.

Kwon et al. [166] developed a system using the combination of a gas leak detector, gateway, absence button, smoke detector and activity sensor to analyse the activity patterns of older people. The algorithm processed these data to decide whether a person may be involved in a dangerous situation. In this respect, the proposed method achieved an accuracy of 80.07%.

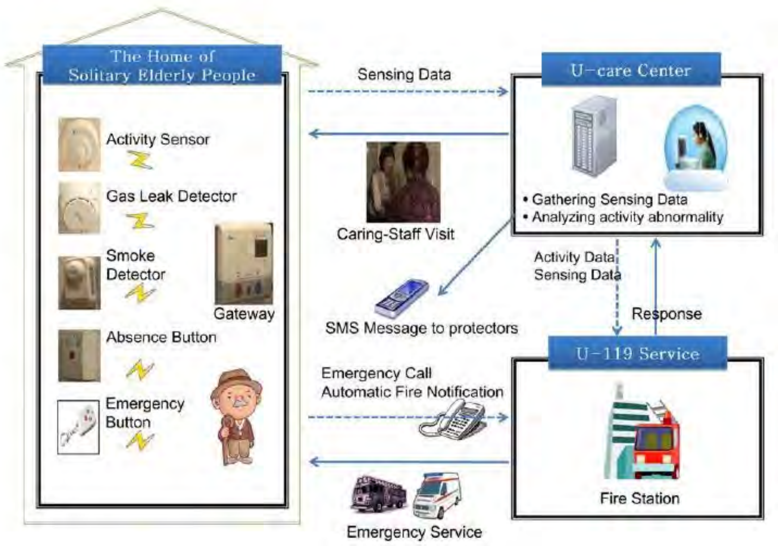


FIGURE 2.5: An overview of unobtrusive system that established in Korea [166].

Logan et al. [168] developed a smart home that consisted of different types of sensors, such as a reed switch sensor, electrical current flow sensor, temperature sensor, humidity sensor, light sensor, barometric pressure sensor, gas sensor, water flow sensor and RFID tag to perform activity recognition. They recruited a married couple to stay in the house for 10 weeks. The couple did their normal daily activities. A 104-hour subset of the collected data were analysed using Naive Bayes and decision tree classifiers. The system was used to classify ADL but only limited success was reported.

The work of the above researchers showed that ambient sensor device can be used for recognising daily activities with some restricted success. The important issue relating to this research is that these activities can include abnormal events as falls and thus ambient sensors placed in judicious positions in a smart home type environment have the potential for being appropriate technology for unobtrusive fall monitoring.

2.7.3 Discussion

At this time the cost and complexity of smart home technologies are too high because a large number of such sensors are needed to comprehensively monitor all the spaces in a living environment. However, in the future, these technologies will become cheaper, smaller, more power efficient and thus more likely to be cost effective and widely deployed.

2.8 Comparison between approaches

The definition of home telehealth technology obtrusiveness so far is not commonly reported in the literature. Hensel et al. [169] addresses some of these issues and suggests a universal classification which includes eight categories of obtrusiveness. Table 2.7 categorises the advantages and disadvantages of the three different approaches to fall detection that have been explored in this chapter.

TABLE 2.7: Challenges and current limitations of automatic fall detection approaches based on universal classification presented by Hensel and other writers [169].

Parameter		Video Analysis	Wearable sensors	Ambient sensors
Physical	Functional dependence	yes	yes	yes
	Discomfort or strain	no	yes	no
Usability	Lack of user friendliness or accessibility	yes	yes	no
	Additional demands on time and effort	no	yes	no
Privacy	Invasion of personal information	yes	no	no
	Violation of the personal space of the home	yes	no	no
Function	Malfunction or sub-optimal performance	dbl	dbl	dbl
	Inaccurate measurement	dsp	dsu	dsp
Human Interaction	Lack of human response in emergencies	no	no	no
Self-concept	Symbol of loss of independence	no	yes	no
	Cause of embarrassment or stigma	no	yes	no
Routine	Interference with daily activities	yes	yes	no
	Acquisition of new rituals	no	yes	no
Sustainability	Concerns about affordability	no	no	no
	Concern about future needs and abilities	no	yes	yes

dbl = depend on the battery lifetime;
dsp = depend on the sensor placement;
dsu = depend on the sensor usage;

2.9 Conclusion

The aim of a fall detection system is to provide immediate attention as soon as a fall occurs to reduce the risk of hospital admission and death [28].

One serious issue related to falls among the elderly living at home or in a residential care facility is the 'long lie' scenario, which involves being unable to get up from the floor after a fall for 60 minutes or more. A proactive solution to reduce the incidence of long lie events is by developing a system that is able to prevent the preceding fall from occurring [31], but progress in this area is slow. The next most appropriate solution to solve this problem is by providing a system that is able to automatically detect the fall as soon as possible after it occurs and subsequently raise an emergency alert.

The chapter summarised some of the wearable and monitoring technologies used for falls detection. Many existing technologies have limitations. For example, the ethical issues behind video cameras in daily use are related to privacy and intrusiveness since movements are typically recorded over the entire day. An alternate means of monitoring is based around wearable technology. A considerable number of studies of accelerometer and gyroscope-based wearable falls detection devices have been cited in the literature. Common issues associated with these wearable devices relate to battery life as well as compliance. For example, several studies stated that people with dementia often do not wear wearable sensor devices in their daily living [147, 159]. Other issues are that many studies report testing with very limited sample sizes and typically in healthy younger cohorts.

In light of the deficits associated with wearable sensors and video camera, some recent research themes have evolved in the direction of using a smart home or residential care environment, often utilising multiple sensor modalities, to unobtrusively detect falls. Ambient sensors provide a mechanism that allows processing of environmental data (such as ambient temperature, pressure, and motion of the person) and ignoring personal identities [157].

One notable study examining the use of ambient sensors to differentiate between falls and daily activities was by Sixmith et al. [170, 171]. In this study, the researchers mounted an array of PIR sensors on the wall to determine activity as well as falls.

The sensors traced a mobile object and gathered the object's information including location, velocity, shape and size. After that the fall detector was able to differentiate daily activity from falls of any kind by observing the collected data. The system worked perfectly for classifying normal activities (a true negative rate of 100%). In contrast, the proposed system only correctly recognised 35.7% of the actual falls with loss of consciousness. The system may have a relatively high false negative rate, but the performance can always be increased by adding more training data.

Some examples of smart homes equipped with multiple sensors include the Gator Tech Smart Home [167], Toyota Dream House PAPI [172] and NICT's Ubiquitous Home [173]. However, the deployment and adoption of real-life smart houses has so far been slow. There has been heavy reliance on hardware development, which was and remains both costly and time-consuming.

This reliance can be mitigated by developing simulation models which can be used to generate sensor signals similar to actual ones. The simulation presented in this reseach enables the evaluation of various scenarios with both simple and complex configurations, obviating the difficulties of developing and deploying sensors. In addition, it gives some distinct advantages during the development phase, prior to hardware prototyping and testing, since it is easy to examine large numbers of scenarios for people with different age, height and BMI ranges.

Indeed it is unlikely that real sensors will match the ideal performance of the sensors simulated here. It is important to first understand how such an algorithm will perform with idealised sensor performance before the degradation of this algorithm in the face of realistic sub-optimal sensor performance is investigated. In the next chapter, the requirements for the design and construction of a fall detection and monitoring simulator are presented in more detail.

Chapter 3

Simulation of a Smart Home Environment

3.1 Introduction

The emergence of technologies to improve quality of life for older people and their families is not a recent phenomenon. Much research has been performed in the field of home monitoring over many years. Older people are living longer and more fulfilled lives, and they desire to live as independently as possible. However, with an independent lifestyle comes risks and challenges, such as falls and their related injuries.

One solution for improving the quality of life of older people involves the development of a smart system to monitor the older people living at home, and their interaction with others and the environment, and to infer the activities performed by these people and their family members, with the intention of enhancing their quality of life and minimising the injuries and deaths caused by falls.

Based on the review presented in Chapter 2, most researchers have tested the use of wearable falls detection devices for monitoring subjects and detecting falls in a laboratory setting [121, 122]. The findings and conclusions of these studies should be further validated by running normal fall trials using wearable sensors in older people's residential centres. However, the recruitment of older adults in a field trial faces major challenges, including their health conditions, social and cultural perspective and potentially impaired capacity to provide important documents [174] i.e. consent form, monthly fall diaries (gold standard method to assure the accuracy of the falls data) for one year and a set of questionnaires. These problems become more complex since people with dementia often forget to wear body-worn devices during daily living [147].

In light of these problems associated with wearable sensors, some recent research has aimed to develop an unobtrusive system that can perform assessment of ADLs for older people in unsupervised home settings [160, 165]. A smart home can be defined as the convergence of service and technology in the home for achieving a healthier life [175]. Several examples of smart homes are Gator Tech Smart Home [167], Toyota Dream House Papi [172] and NICT's Ubiquitous Home [173].

Dewsbury et al. [176] illustrated what challenges are present in smart home development by considering technical as well as social aspects. The authors discussed the issues arising from the development of smart home technologies such as technical questions of sustainability, system maintenance and reliability; and social concerns about the design issues that relate to privacy management and the acceptance of technology. Moreover, smart homes are difficult to deploy and test; not to mention their costly infrastructure (such as furniture and home appliances). Further, there are no existing algorithms to interpret signals derived from sensors placed in the smart home to track multiple people and to unobtrusively infer activities accurately.

Several initial studies have previously investigated aspects of this topic. For example, Noury et al. [177] and Lee et al. [178], focused on monitoring the movements of older people in different rooms using passive infrared (PIR) sensors and subsequently modeling their ADLs. Subsequent research by Chan focused on static and mobile sensors that collect multiple types of data to monitor the health status of older subjects [179]. However, the above-mentioned implementations are typically designed for the use of a single subject and not suitable for multi-person households.

This chapter will focus on options to reduce the complexity and cost of designing and evaluating smart homes by developing a residential environment and ambient sensor simulator that can respond to different movements of people. The output data from the simulator will be used for the construction of a fall detection algorithm.

Section 3.2 describes the related literature and research work in terms of their methodology and apparent drawbacks. Sections 3.3 and 3.4 describe a methodology for the design and implementation of a simulated smart home environment populated by simulated residents and equipped with simulated ambient sensors. Finally, in section 3.5, conclusions are drawn from the discussions which will lead to algorithm development for distinguishing falls from ADLs for a single person living alone.

3.2 Related research

There have been many advancements in this field of research and more are underway. Consequently, various simulators for pervasive or ubiquitous computing have been proposed, such as PlaceMaker [180], V-PlaceLab [180], VPlaceSims [180] and smart house simulator [181].

PlaceMaker [180] is software for creating two-dimensional (2D) or three-dimensional (3D) floor plans and generating a connectivity matrix which represents the interconnections between rooms. V-PlaceLab [180] is a simulator that has the ability to create different activities for the residents in the home. VPlaceSims [180] is a game engine that allows the user to navigate their avatar through the space, exploring their environment and communicating with other avatars and objects. This simulator does not consider sensor simulation.

Smart house simulator [181] is a virtual reality test-bed that allows programmers to design a smart house equipped with a variety of sensors such as power, temperature, light and location sensors. The user can change the current state of sensors, e.g., the lighting status in a room can be represented by two states, namely ON and OFF.

It must be noted that their idea of creating 2D floor plans and generating realistic schedule for each resident in the home are something we are also using. However, all of these implemented simulators can not simulate the ambient sensors which respond to the subject's movement.

To address this problem, we propose to create simulation tools for simulating the environment and the sensor activations. We use a graphical editor to model the layout of the smart home and the sensors, and use a simulation framework to enable researchers to evaluate various scenarios with both simple and complex configurations. This helps to speed up the algorithm development process and hence reduce the time required for hardware prototyping and field trialing.

3.3 Map editor

The map editor software described in the following was written in Java SE version 7.0. The list of classes that the software contains and a representative example of the Javadoc software documentation can be found in Appendix A. Map Editor.

3.3.1 The design requirements

The function of the map editor is to allow the researcher to manually draft maps of the floor plan of the home, and also show the location and orientation of the sensors of which the WSN consists. This software application provides the possibility to draw something on canvas by providing a tool-box with various tools for drawing different types of ambient sensors (PIR and PM sensors), rooms (rectangular or polygonal), doors and furniture. Users can modify each of those shapes and change their properties; i.e, coordinate systems, size and dimensions. Table 3.1 contains a list of requirements for this editor.

Table 3.1: The summary of the simulator requirements.

No.	Requirement
1	Design user-friendly graphical user interface (GUI).
2	Design a class hierarchy to represent shapes that may be drawn on a canvas.
3	Show grids which can be used as a drawing aid.
4	Ability to select shapes by clicking with the mouse.
5	Translate shapes by dragging with the mouse.
6	Rotate a shape by using the rotation handle or typing an angle.
7	Change the properties of shapes (i.e., length and width).
8	The functionality to add text.
9	The functionality to zoom in and out.
10	The implementation of scalable vector graphics (SVG) export functionality.
11	Use extensible markup language (XML) as native file format.

3.3.2 Interactive GUI

The map editor will provide a simple GUI as shown in Figure 3.1. The options available in the "file" menu allow the user to create a new floor plan including placement of sensors, load a floor plan file that has been previously produced by the map editor, store the floor plan into an XML file and exit from the application.

The editor provides a palette of seven tools to draw something on a canvas: the room tool; multi-side room tool; door tool; motion detector tool; pressure mat sensor tool; furniture tool; label tool and those that change the properties of objects; and the select tool. Various simple shapes are drawn on the canvas area by clicking the mouse at some point within the canvas. After the first click, as the mouse is moved, a partial shape is rubber banded and follows the motion of the mouse. When the right size is finalized, the shape is generated on the canvas by clicking the mouse. The tool also enables the user to move, rotate, and change the size of the shapes.

Creating a new floor plan

- Each room can be drawn as either a rectangular or polygonal shape. The size of each room can be adjusted by clicking and dragging on a corner of the room or by editing via the property menu.
- Doors are represented as a single straight line. The direction and size of the doors can be changed via the property menu.
- Furniture is drawn as a rectangular shape. The dimensions of the furniture can be changed by filling out the length (l), width (w) and height (h) in the property menu of the object. The user can also change the furniture's orientation in the room to horizontal, vertical, or diagonal directions by rotating the furniture to the right direction or by filling out the degree of rotation in the property menu.
- PM sensors are drawn as rectangular objects. The dimensions of the PM sensor can be adjusted by changing the width (w) and the length (l) of the sensors. The user can set the vertical distance from the PM sensor to the ground, since it can be placed on all chairs and beds, the sofa, in the bathroom in front of the shower and behind the door at the entrance to the unit.

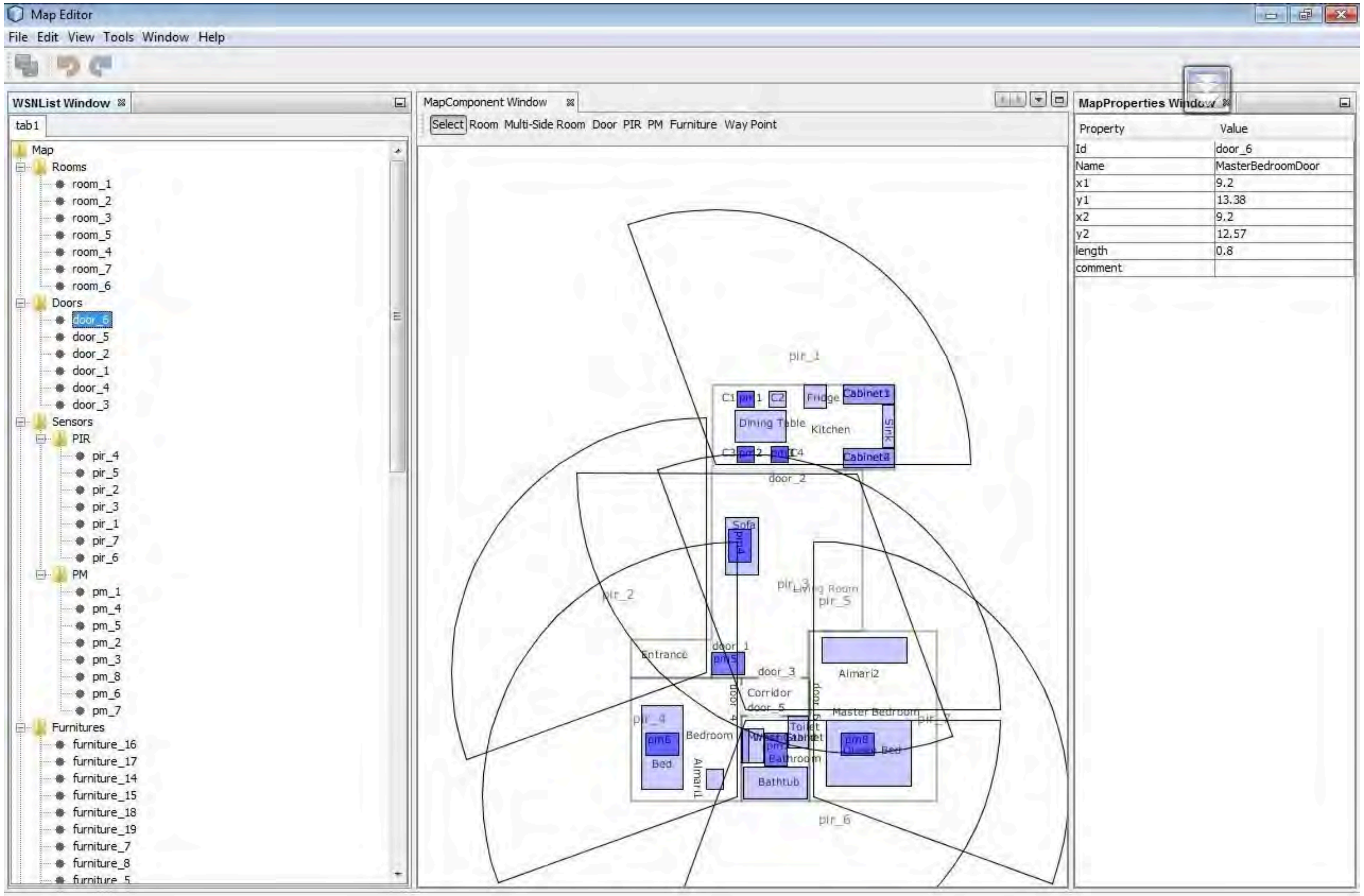


FIGURE 3.1: The map editor is an application that is used to create 2D drawings of sensor locations and residential floor plan.

- PIR motion detectors are drawn as a sector of a circle. The field of view of sensor can be changed by updating the angle value. The user can set the vertical distance from the PIR sensor to a ground, since it can be mounted at different heights on the wall.

- The name of any drawing object on the canvas can be changed by inserting the updated name into the property menu. The orientation of the name can be adjusted by choosing one of the possible values from: 0°, 90°, 270° and 180°.

The editor also provides a display on the interface that lists all the regular shapes in the floor plan, including rooms, doors, sensors, furniture and labels that have been drawn on the canvas.

Store and load the floor plan

The editor is able to convert any shape that has been drawn on canvas to an XML representation and save it into .xml file to prevent the loss of work. Each canvas maintains an array list of shapes which is updated when a new shape or text is added on the canvas. The following XML code shows XML representations of each shape.

```
<svg>
    <g id="map">
        <g id="wall_door_group">
            </g>
        <g id="sensor_group">
            </g>
        <g id="furniture_group">
            </g>
        <g id="label_group">
            </g>
    </g>
</svg>
```

`<svg> </svg>` includes XML representations for any shapes drawn on the canvas. Each shape has it own attributes. For example, for label, the XML representation will consist of x and y coordinates `x="402.0" y="562.0"`, fill and fill-opacity `fill="black" fill-opacity="1"`, font-family and font-size `font-family="Verdana" font-size="10"`, the identification number of label `id="wp_pm_8"`, and finally its

TABLE 3.2: Overview of attributes for each of graphics shape.

Group	Shape	Attributes
`wall_door_group`	wall	id, x, y, width, length, fill, stroke, stroke-opacity and stroke-width
	door	id, x1, x2, y1, y2, stroke and stroke-width
`sensor_group`	PIR motion detector	id, d, z1, z2, fill, stroke and stroke-width
	pressure mat sensor	id, x, y, width, length, height, fill, fill-opacity, stroke and stroke-width
`furniture_group`	furniture	id, x, y, width, length, height, fill, fill-opacity, stroke and stroke-width
`label_group`	text	id, x, y, fill, fill-opacity, transform, font-family and font-size

orientation `transform="rotate(0 216.0 562.0)"`. The summary of attributes for each shape is listed in Table 3.2.

The existing floor plan can be loaded onto the canvas with Uniform Resource Identifier (URI) property. The map editor maintains the scale of the map when a user loads the file.

3.4 WSN simulator

The simulator must have the capability to allow users to create a resident profile and a list of activities for each resident in the home environment. With these features, it is possible to collect various output signals from a number of ambient sensors, placed around the home which are related to specific activities, such as daily activities, a fall from bed after waking up, a fall after getting up from a chair, and a fall when walking or standing.

For generating large amounts of data that incorporate specific activities performed by different people, the simulator should able to automatically repeat the simulation

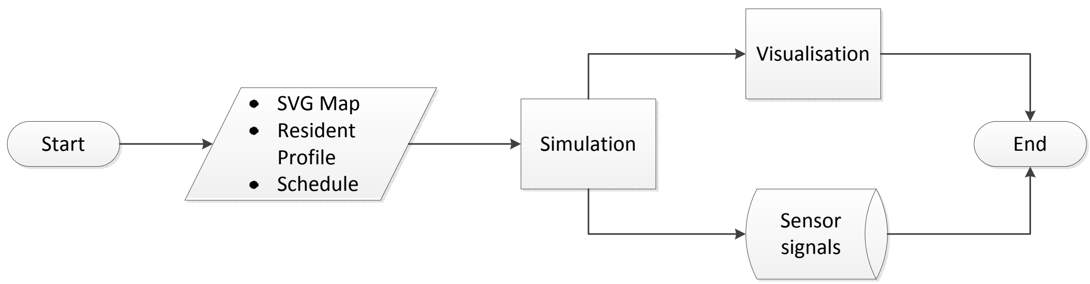


FIGURE 3.2: A flowchart of the simulation software. First, a XML file is loaded containing the existing residential map and creates resident profiles and their activities before the simulation begins. The simulation is started by selecting the Simulate command. The room coordinates from the residential map are examined by the WSN simulator, then the residents' movement is simulated by a path-finding algorithm (A*) through a residential environment. The PIR and PM sensors respond to the movements and produce binary outputs, indicating the presence of activity in defined locations. The output signals from the WSN simulator can be saved with the same name as the XML file (but with the extension .xls) in the same folder. The WSN simulator provides visualisation capabilities including animation of resident movement and interaction with sensors.

process and store the results into a database. These repeated simulations are taken to provide an insight into variations that may be occur in a real-world environments and factors effecting the accuracy, sensitivity and reliability of the system.

The simulation software described in the following was written in Java SE version 7.0. The list of classes that the software contains and a representative example of the Javadoc software documentation can be found in Appendix B. WSN Simulator.

3.4.1 Proposed physical WSN

The following sections describe the real hardware sensors which the simulated WSN (described later) will attempt to emulate.

Motion detectors

Infrared (IR) radiation is a part of the electromagnetic (EM) spectrum with a wavelength ranging from 0.750-1000 μm [182]. This infrared radiation can be further subdivided into sub-bands as follows [182]:

- Near-infrared (NIR, IR-A DIN): 0.75-1.4 μm
- Short-wavelength infrared (SWIR, IR-B DIN): 1.4-3 μm
- Mid-wavelength infrared (MWIR, IR-C DIN): 3-8 μm
- Long-wavelength infrared (LWIR, IR-C DIN): 8-15 μm
- Far infrared (FIR): 15-1000 μm

Although infrared radiation is not visible, humans can sense it as heat. Thermal radiation emitted by a body is mostly within the infrared region. Even at room temperature or below room temperature, bodies emit significant amounts of long-wavelength infrared light, which can be used for human tracking [183].

The human body is a natural heat source, with an average temperature of 37 °C, or 98 °F [158]. Temperature differences between human bodies and their environment create a constant heat exchange. The object's radiation characteristics can be

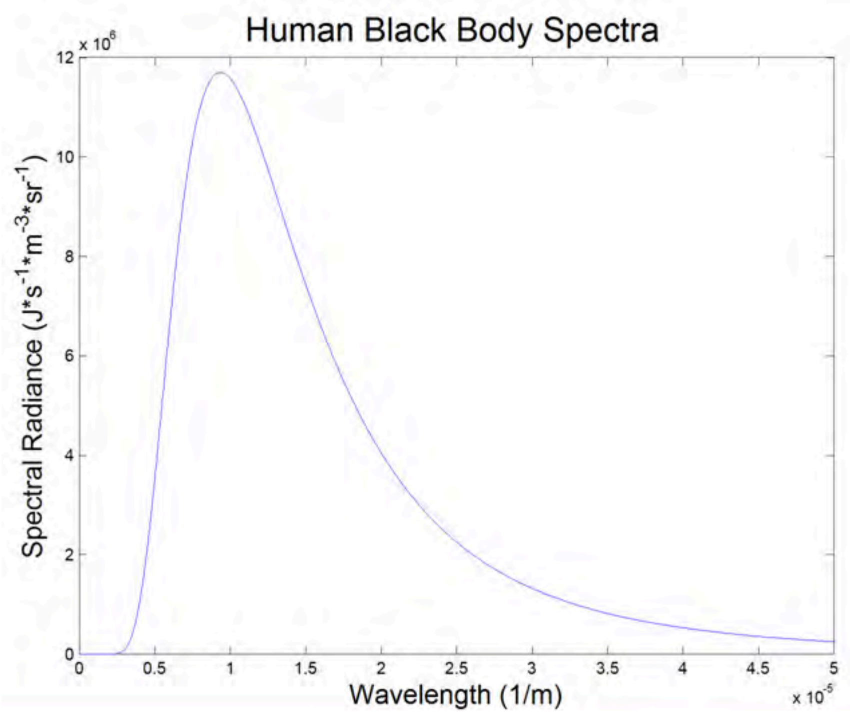


FIGURE 3.3: The specific peak emission wavelength of the human body or any material can be calculated using the Planck radiation formula [184].

analyzed using a formulation of black body radiation derived by Max Planck [185]. The black body radiation curve for a typical human body is shown in Fig 3.3. As is obvious from the figure, it can be seen that that a human body emits radiation in the 5-14 μm wavelength range with the peak at 9.4 μm [184]. The PIR detector which is sensitive to radiation with a wavelength range of about 10 μm would be able to detect human presence and their activities within the detection range/coverage area [185].

Other characteristics that might be considered for movement detection are the velocity and the type of movements. Findings from the literature show that the preferred speed of walking and running in normal-weight adults of both sexes are approximately 1.4 m/s (5 km/h) [186] and 10 m/s (36 km/h) [187], respectively. The PIR detectors must be able to distinguish these types of movement at different speeds.

An example of a PIR detector in this research is a digital type motion sensor (AMN41121, Matsushita Electric Works Ltd, Japan). The Matsushita Electric Works Ltd website claims that their PIR detectors have been researched and should provide the ability to have low current consumption while maintaining a minimum threshold to accommodate a better sensitivity and to achieve a wider coverage area [188].

A PIR sensor comprises a built-in amplifier, comparator for digital output, power stabilizer, quad PIR element and optical filter. The quad PIR element allows the sensor to track movement when the subject is moving in the horizontal or vertical plane [189].

Standard PIR motion detectors (MP Motion Sensor NaPiOn, Panasonic Electric Works Co., Ltd.) do not have uniform coverage but instead have a complicated 3-dimensional pattern of wedge-shaped detection zones projecting outwards from the sensor, with dead zones between them, caused by the geometry of the sensor's Fresnel lens. This PIR detector is covered by a Fresnel lens comprising 16 separate angled surfaces with a single focal point and with five optical axes, so that there are 64 detection zones monitored by the lenses [188], as shown in Fig 3.4.

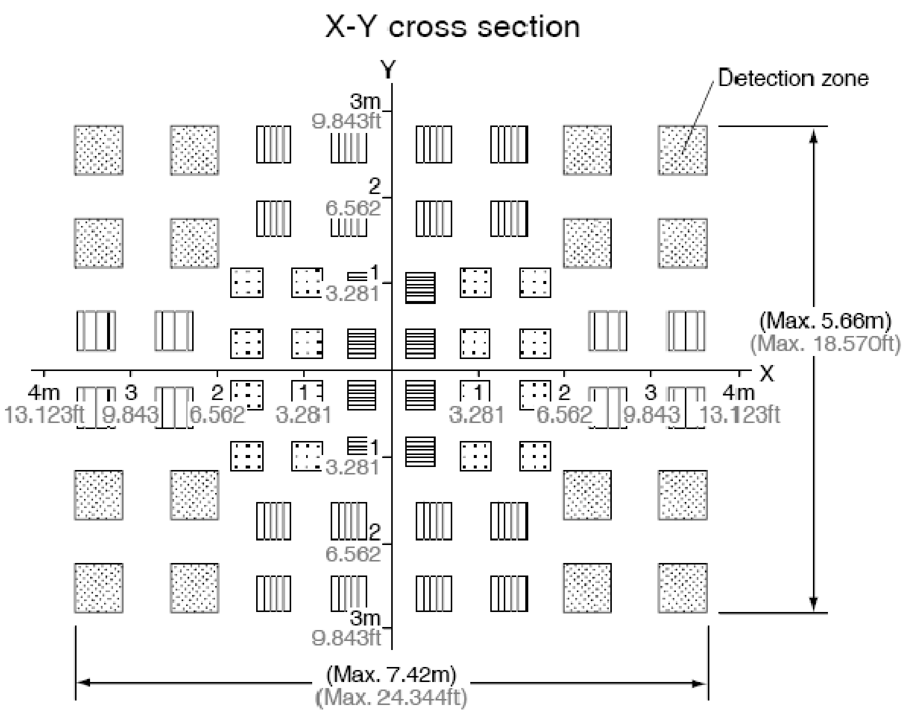


Figure 3.4: Vertical cross-section of standard type PIR sensor, from its data sheet [188].

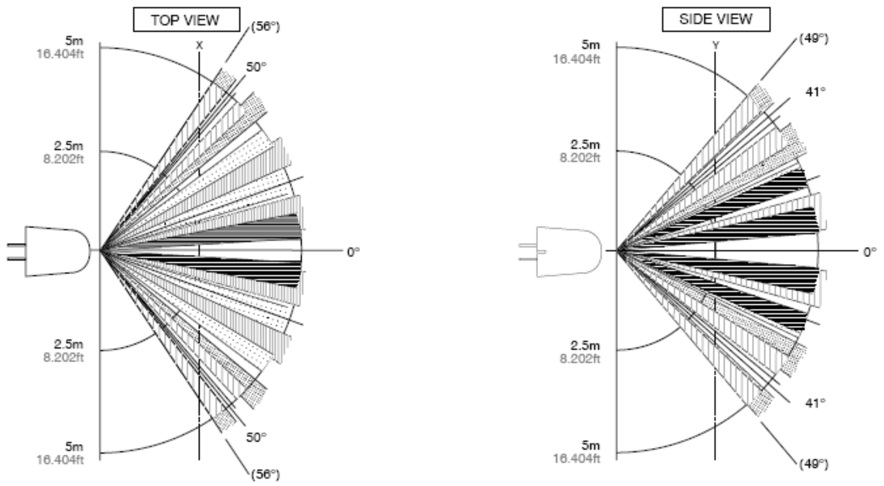


FIGURE 3.5: Orthographic projections of the detection zones of a PIR sensor, from its data sheet [188]. PIR sensors contain dead zones in between their sensitive zones and are less sensitive to movement at greater distances from the sensors. Moreover, these sensors may not be active when a person moves towards or away from the sensors.

Also, the sensitivity of the PIR motion detector to movement decreases with distance from the sensor, due to reduced thermal energy reaching the sensor. These detectors are not sensitive to movement directly towards/away from them and require movement of the heat source across the detection zone to be triggered. In this manner, one can monitor the movements of humans (and possibly pets) with a detection range of 100° in the azimuth, ±82° in the elevation, and up to a distance of about 5 m as shown in the Fig 3.5 [188].

Pressure mats

The PM sensor is assumed to be a contact switch, generating a logical true value when someone steps on the mat (or some other pressure is applied to the mat) [190].

3.4.2 The input for simulator

The WSN simulator generates sensor signal data sets based on three main inputs: the grid data structure (an internal representation of the SVG map), the resident profiles and the scheduler data structure.

Grid data structure

The simulation software tessellated the residential area into a square grid with a resolution of 2.5 cm, on which diagonal movement was also allowed. This simulation grid is automatically generated by analysing the floor plan of a residential map. Each grid may have an associated score with it. A grid consisting of obstacles (i.e., walls or furniture) will have a bigger cost.

Resident profile

Each simulated person has their own personal information including name, gender, age, height and walk speed. Realistic walking speeds for the simulated persons are calculated using six-minute walking distances (6MWD) [191]. The 6MWD can be approximated with the following equations. For men: 6MWD = 1,140 m - (5.61 $\times$ BMI (kg/m^2)) - (6.94 $\times$ age (year)). For women: 6MWD = 1,017 m - (6.24 $\times$ BMI (kg/m^2))- (5.83 $\times$ age (year)). Here, BMI is body mass index [191].

The following XML code shows a skeleton of a resident profile:

```
<people>
    <person age="67" gender="MALE" height="1.78" name="people1" speed="1.37"/>
    <person age="60" gender="FEMALE" height="1.55" name="people2" speed="1.36"/>
    <person age="62" gender="MALE" height="1.71" name="people3" speed="1.43"/>
</people>
```

Scheduler data structure

A schedule is used to test various possible combinations of daily activities and abnormal events such as falls; so different sensor responses to human movements can be simply evaluated. One of the major benefits of a schedule module is its ability to create different activities for each resident in the home.

A schedule consists of one or more scenarios, each of which contains one or more events. A scenario can be considered as a generic container, it is up to the user how they want to logically group the events between scenarios.

An event has a start and end time. The user should specify this in the format of *hh*:*mm*:*ss*, where *hh* is the hour, *mm* is the minutes, and *ss* is the seconds. The simulator will set a default start time for each person (note: all persons must start at the same time). The end time is automatically calculated depending on the task type or the duration of the event. The event duration is calculated when a person moves from one place to another place and is specified when a person is motionless (standing, sitting, or lying).

For each event, the user should specify start and destination places to allow the pathfinder to bring the person from one place to another. These places are inserted using the 'way point' attribute.

The following XML code shows a skeleton of a scheduler profile:

```
<scheduler>
    <scenario description="scenario31">

        <event duration="120000" person_id="people1" start_time="07:30:00" task="↩
    Mobility" task_type="Lying_Down_Trigger_Sensor" timing_type="Task_Duration" ↩
    way_points="{wp_furniture_19}"/>

        <event person_id="people1" task="Mobility" task_type="Walking" ↩
    timing_type="Mobility_Duration" way_points="{wp_furniture_19,wp_room_1}"/>

    </scenario>
</scheduler>
```

3.4.3 Simulation engine

The following sections describe the approximations made to simulate the physical environment and sensor responses. Also described are the models for simulating human movement and complex scenarios.

Simulating motion detectors

The PIR motion detectors, described in section 3.4.1, are assumed to be sensitive within 64 detection regions, spread uniformly over 100° in the horizontal plane. They are considered to be infinitely sensitive to any movement within these detection zones, at any speed in any direction.

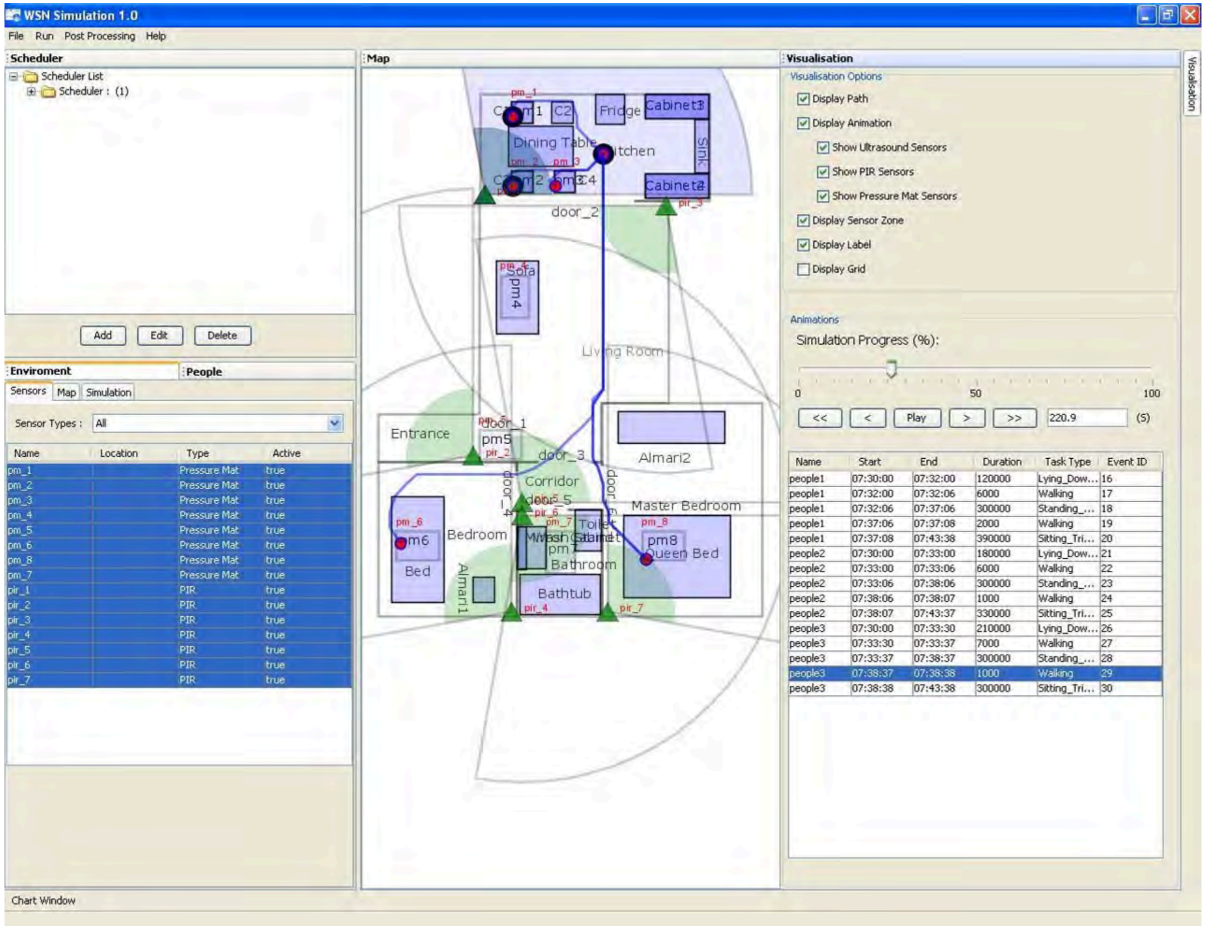


FIGURE 3.6: Show is the GUI of a Java-based wireless sensor network (WSN) simulator software. This simulation reads the room coordinates from a residential map, a path-finding algorithm (A*) simulates the subject's movement through the residential environment, and PIR and PM sensors respond in a binary manner to the subject's movement.

There are two factors that affect the PIR sensor state (ON/OFF): the PIR sensor area coverage (angle of view, orientation, radial distance from the sensor) and line-of-sight. Line-of-sight can be defined as a direct path free of obstacles between the PIR sensor and the warm object [192]. If a person enters the detection zone of a PIR sensor in a specific area and within a line-of-sight, the sensor state will change to ON. If a person leaves the detection zone of a PIR sensor or enters an area which does not have line-of-sight to the sensor, the sensor state will change to OFF.

When the subject is standing or sitting in the same location and performing an activity, all motion detectors within a line of sight will activate even if the subject is not changing their position. Also, when the subject is lying down or crawling on the floor, all motion detectors within line of sight will activate (provided they are not obscured by furniture). Moreover, when the subject is motionless (lying down, sitting or standing), all motion detectors within line of sight will deactivate.

The activation of a detector is also assumed to be unaffected by the direction in which the person is facing; for example, the motion detector can still be activated by arm movements even though the person has their back turned to the PIR motion detector while standing in the kitchen preparing food.

Simulating pressure mats

The PM generates a logical true value when the simulated agent is within its sensitive area. The sensors are assumed to have an infinitesimally low threshold, but in reality this could be tuned to some offset value. There is one factor that governs the PM sensor state (ON/OFF): the active area of the PM sensor. If a person enters the active area of the PM sensor, the sensor will be ON.

Simulating movement

Simulated residents enter the home with the knowledge of the home's floor plan. They recognise the locations of all furniture so that they can seek them out when they want to lie or sit down. They also know which grids contain walls that they need to avoid when moving from one room to another. Then, each of simulated residents need to travel by the shortest path to go directly to their destination using the A* search algorithm.

The A* algorithm was first introduced in 1968 by Peter Hart, Nils Nilson, and Bertram Raphael [193] and is used widely in game development [194]. This algorithm was based on a combination of Dijkstra's algorithm and the Best-First-Search algorithm. The generation of realistic subject movement begins by specifying an initial coordinate and destination coordinate and then constructing the shortest allowable path between the two points by using the A* pathfinding algorithm [194].

The first step in pathfinding is to divide the search area into a grid (a square shape). Give each grid a score with this equation [195]:

$$F = G + H \tag{3.1}$$

where:

- G represents the cost of movement from the initial point to the current grid.
- H represents the estimation cost of movement from the current grid to the destination point.
- F is the estimation of total cost from the initial point to the destination point.

The pseudocode of the A* algorithm is described in more detail below:

1. The execution begins by adding the initial point to an open list.
2. Repeat the following steps to find the shortest path:

   a Get the grid point from the open list that has the lowest distance from the initial point.

   b Remove the grid point from the open list and add the grid to the closed list.

   c For each of all neighbouring grids:

   - If it was not listed on the open list, add the grid to open list and then make this grid point child of the current node. Subsequently store the F, G and H costs of the grid point.

- If it was already listed on the open list, find out whether this path to that grid point was better by measuring the G cost. A lower cost implies a better path. If so, switch its parent to this grid and perform the calculation process for all costs (the F, G and H costs).

3. Terminate the process and save the path when:

   a The destination point is finally added to the closed list, in which case the path to the destination has been found.

   b There were no more left grids in the open list indicating there was no path between grids that could be found.

The way to calculate the G and H scores of the grid is shown in Figures 3.7-3.8.

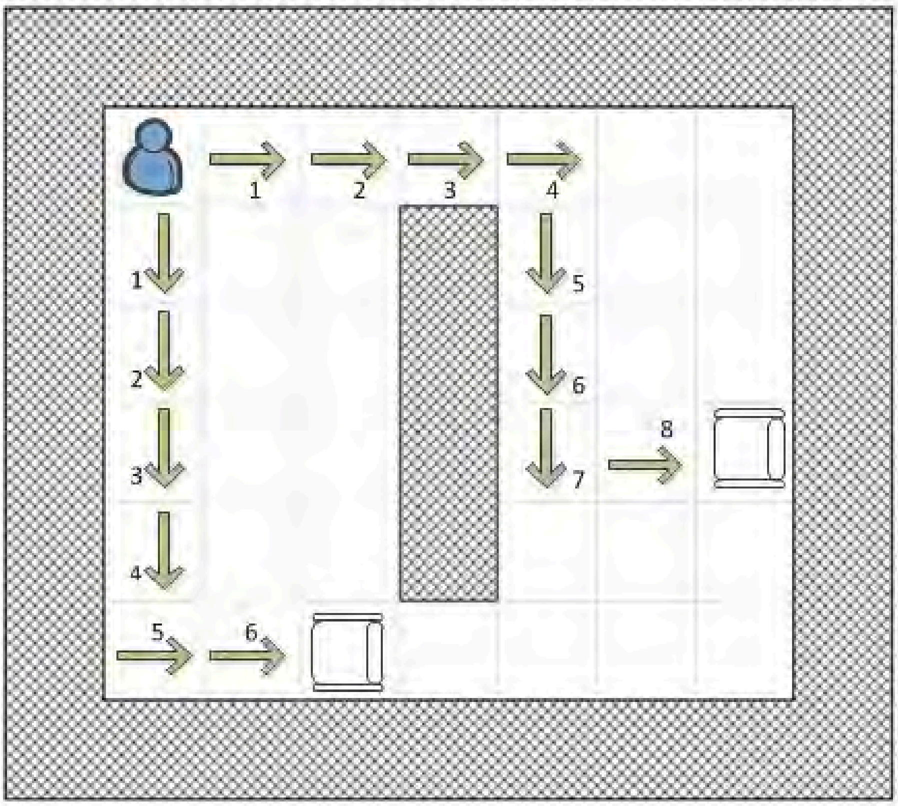


FIGURE 3.7: Shown are the two routes to two different locations of a chair, with the G score of each tile listed on the tile. The G score would be 1 for a grid point adjacent to the start point, but this G score will increase as the subject moves further away from the start point.

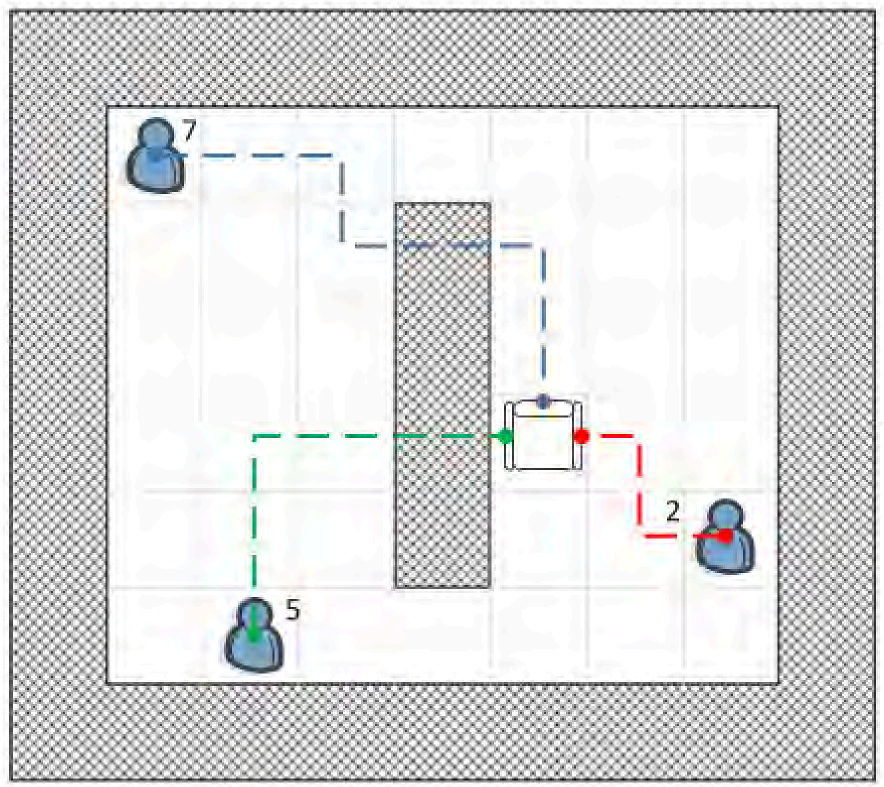


FIGURE 3.8: Shown here is the use of "Manhattan distance method" to estimate H score from various initial and destination points. The method works by calculating the remaining number of vertical and horizontal grid points to reach the destination point and ignoring any obstacles (such as walls or furniture) that may be in the way.

3.4.4 The output from simulator

Each time a simulation is executed, the simulation profile is stored as an XML file. Sensor signals, sampled at 5 Hz, are stored in the database and then exported into an Excel spreadsheet for further analysis. The data can be time-based or event-based, as shown in Fig 3.9 .

Start Time	End Time	SensorID		SensorCondition	SensorType
07:30:00.200	07:32:00.400	pm_8		1	2
07:30:00.200	07:32:01.200	pir_7_lower		1	1
07:30:00.200	07:33:00.400	pm_8		1	2
07:30:00.200	07:33:01.200	pir_7_lower		1	1
07:32:01.200	07:32:04.000	pir_5_lower	pir_5_upper	1	1
07:32:02.400	07:32:05.000	pir_3_lower	pir_3_upper	1	1
07:32:05.200	07:32:05.800	pir_1_lower	pir_1_upper	1	1
07:32:06.000	07:43:38.000	pir_1_lower	pir_1_upper	1	1
07:33:01.200	07:33:04.000	pir_5_lower	pir_5_upper	1	1
07:33:02.400	07:33:05.200	pir_3_lower	pir_3_upper	1	1
07:33:05.200	07:33:05.800	pir_1_lower	pir_1_upper	1	1
07:33:06.000	07:38:07.600	pir_1_lower	pir_1_upper	1	1
07:37:07.400	07:37:07.600	pm_1		1	2
07:37:07.800	07:43:38.000	pm_1		1	2
07:38:06.400	07:38:06.800	pm_3		1	2
07:38:07.000	07:38:07.600	pm_2		1	2
07:38:07.800	07:43:38.000	pm_2		1	2
07:38:07.800	07:43:37.800	pir_1_lower	pir_1_upper	1	1

FIGURE 3.9: The output signals from WSN simulator shown in this figure are event-based signals.

3.4.5 Visualisation

An XML parser such as DOM (Document Object Model) is used to build a visual representation of XML objects when loading the map. The process is performed by searching for the keyword for each shape while reading the XML file.

The visualisation would show the simulated resident walking across a room; instead of trying every possible route in advance, the simulated resident would generally walk along the shortest path to the destination and avoid an obstacles such as walls or furniture. The appropriate sensors will be switched ‘ON’ each time the simulated residents move within their coverage area.

3.5 Discussions and conclusions

Since hardware development is time consuming and expensive, a WSN simulation gives some distinct advantages during the development phase, prior to hardware prototyping and testing. The developed simulation provides the capability to test various scenarios with from simple to complex configurations. This simulator could help researchers to better understand how the sensors respond to a variety of simulated resident movements. Environmental characteristics such as the number of sensors, subject mobility and line-of-sight can be analyzed. It will also enable researchers to focus primarily on the algorithm development.

The simulator's ability to display the layout of the floor plan could be used as preliminary validation of configuration of sensors in the residential area before starting the real process of installation. By selecting the placement of ambient sensors on a particular floor plan, the user can see the coverage area of each sensor. Since the simulation model is highly repeatable unlike experiments with real sensor networks, algorithms can be tested and their relative advantages over one another can be judged objectively [196].

The next chapter will focus on the process of algorithm development for the accurate detection of falls with a single simulated resident.

Chapter 4

Simulated Unobtrusive Falls Detection for a Single Person Living at Home Alone

4.1 Introduction

As stated earlier in Chapter 2, night time falls occur more frequently than day time falls [197]. In residential aged care facilities about 54% of falls occur at night time when older people make a trip to the toilet [198]. Another study has found that about 76% of older people staying in hospital rooms reported falls when they are attempting to go to the toilet during the night [199].

Accelerometer and gyroscope-based wearable falls detection devices are often used by researchers to attempt to detect falls when they occur. However, when a subject moves around the home at night-time, such as to make a trip from the bedroom to the toilet, it is unlikely that they will remember or even feel an inclination to wear such a device [17].

This chapter focuses specifically on the investigation of the potential effectiveness of using simulated responses from PIRs and PMs to unobtrusively detect falls when they occur (most likely during the night time) among older subjects aged 45-87 years who are living alone at home.

Section 4.2 describes the methodology used in this chapter. The experimental model describes the simulation model in detail including the floor plan of the residence, the locations and orientations of the sensors, the generated simulated scenarios and the profile of residents. There are three possible scenarios preceding a fall event: a fall from bed when sleeping; a fall from a chair when sitting; a fall when walking or standing [86]. These three scenarios are simulated using a 2D simulation of a single subject navigating their way through a series of activities (including some simulated falls) in a residential unit; this is achieved using the simulator software described in Chapter 3. The data generated by the PIR and PM sensors as the subject moves through the environment are captured. A simple heuristic decision-tree classification paradigm is applied to the acquired data to discriminate falls events from normal activities.

The performance analysis performed is presented in Section 4.3 and the discussion of the results is presented in Section 4.4. Finally, in Section 4.5, the conclusions are drawn from the discussions which will lead to possible improvements in the fall detection system and algorithm design, which are incorporated the falls algorithm and the simulation model and presented in Chapter 5.

4.2 Methodology

4.2.1 Experimental design

Residential environment

The floor plan of the residential unit includes two bedrooms, a bathroom, corridor, living room, kitchen, and entrance hall. Each bedroom has one bed and one wardrobe. The bathroom has a shower, sink, toilet and wall storage cabinet. The living room has one sofa. The kitchen has a dining table with four chairs, a refrigerator, a kitchen sink, two wall cabinets and two floor cabinets. The floor plan is shown in Figure 4.1.

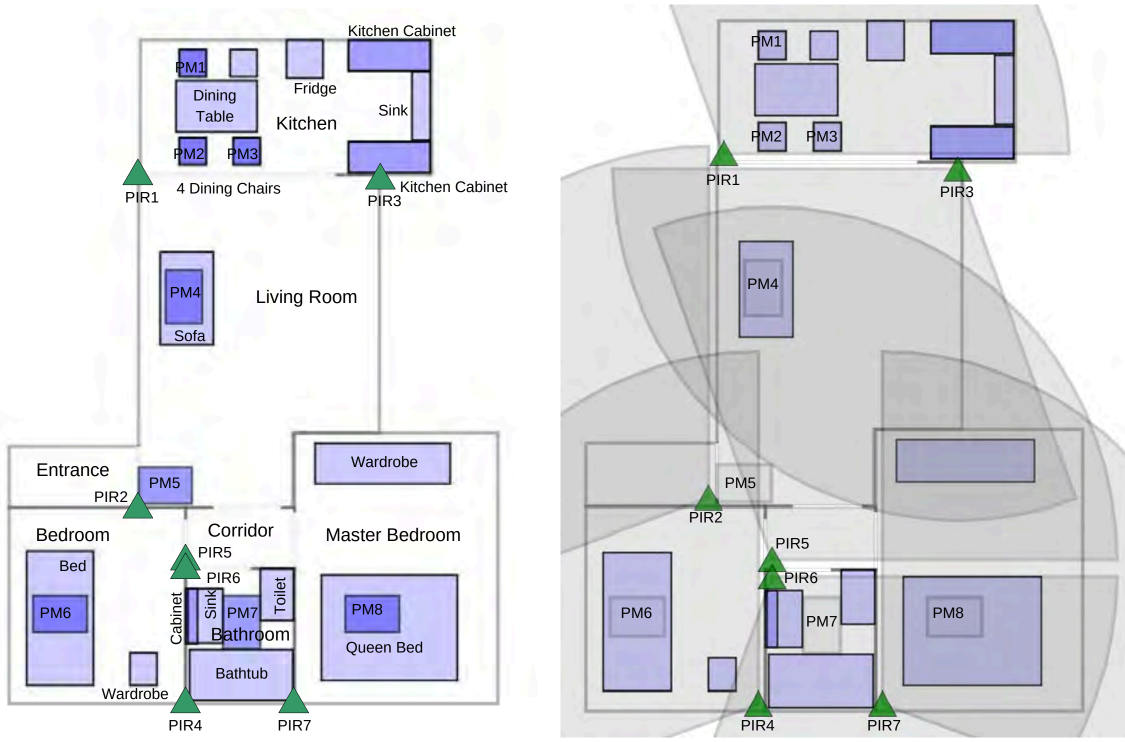


FIGURE 4.1: Floor plan of the residential unit showing all rooms and sensitive regions of the ambient sensors (the PIR motion detectors and the PM sensors). The left image shows the room layout, furniture and sensor placement. The right image indicates the plan view of the PIR sensitive regions, given their placement in the residence.

Sensor placements

One PIR motion sensor is placed on the wall of every room. Rectangular PMs, with sizes ranging from 0.16 m^2 to 0.42 m^2, are placed on all chairs and beds, the sofa, in the bathroom in front of the shower and behind the door at the entrance to the unit.

Resident profiles

The simulator produces a number of different scenarios, containing simple scenarios with single person. About half of the sample were men (108 out of 160, 0.675%). Age was selected randomly from a uniform distribution over the interval [45,87] years. Random BMI and height parameters are also randomly generated using a normal distribution with means and standard deviations drawn from published population statistics [200], as shown in Table 4.1. The average simulated walk speed, calculated from these ages and BMIs, is almost equal to the preferred speed of walking in normal-weight adults of both sexes, which is approximately 1.4 m/s (5 km/h) [186]. These distributions are generated using MATLAB version 7.5 (The MathWorks, Natick, MA, USA). The MATLAB code can be found in Appendix C. List of MATLAB Code.

TABLE 4.1: Mean and standard deviation of measured height and BMI in middle-aged and older individuals in Australia [200].

	Male	Female
Parameter	mean (SD)	mean (SD)
Height (cm)	175.03 (6.79)	161.62 (6.26)
BMI (kg/m^2)	28.51 (4.13)	27.68 (5.54)

ADL and fall scenarios

The fall detection algorithm was tested for four scenarios, one scenario including a normal ADL and three scenarios with falls. The three falls scenarios are: (i) the subject was sleeping and falls from the bed; (ii) the subject was sitting and falls from a chair; (iii) the subject was walking or standing and falls in different rooms [86]. The scenarios are listed on a case by case basis in Table 4.2.

Each normal scenario can be a sequence of one or more ADLs including walking, sitting on a sofa or chair, climbing into bed, preparing meals, showering and leaving the home. The aim of simulating these scenarios is to analyse the false positive rate of the system.

In the scenarios that involve falls, three types of post-fall scenario will be simulated:

- Fall with successful recovery: the subject falls onto the floor but is able to recover by crawling to the furniture (chair, sofa, bed) and sitting on the furniture for two minutes before trying to move again.
- Fall without loss of consciousness: the subject falls, remains conscious, and unable stand up for about seven minutes.
- Fall with loss of consciousness: the subject moves to a particular location, experiences a fall, and then remains unconscious on the floor for seven minutes.

TABLE 4.2: Scenarios for ADLs or falls involving one person.

Type of scenario	Time	No.	Scenario description	Total Correct	Total Incorrect	Accuracy (%)
ADLs		**I**	**Normal ADLs without falls**			
	Day time	I.1	Subject goes from the master bedroom to the kitchen to a prepare dinner. Subject sits on the dining chair and starts eating.	10	0	100
	Day time	I.2	Subject takes out the kitchen trash, leaves the home and enters the home back after 3 minutes.	10	0	100
	Day time	I.3	Subject packs bag for shopping in the master bedroom and then leaves the home.	0	10	0
	Night time	I.4	Subject goes from the kitchen to the living room. Sits motionless on a part of the sofa that is *not* covered by a PM sensor.	10	0	100
Fall from bed		**II**	**In the master bedroom, subject falls from the bed to the floor (lying on the floor) near the bed, then:**			
	Night time	II.1	Subject is able to get up from floor after fall, then goes from the master bedroom to the bathroom.	10	0	100
	Night time	II.2	Subject remains conscious and moving, but is unable to stand up for 7 minutes.	0	10	0
	Night time	II.3	Subject experiences unconsciousness for 7 minutes.	10	0	100
Fall from chair		**III**	**Subject is sitting on the dining chair. Tries to get up from the dining chair and then falls to the floor, then:**			
	Night time	III.1	Subject is able to get up from floor after fall, then sits back on the dining chair.	10	0	100
	Night time	III.2	Subject remains conscious and moving, but unable to stand up for 7 minutes.	0	10	0
	Night time	III.3	Subject experiences unconsciousness for 7 minutes.	10	0	100
Fall when walking		**IV**	**Subject washes dishes after dinner. Subject then walks from the kitchen to the sofa in living room, falls before reaching the sofa, then:**			
	Night time	IV.1	Subject then crawls along the floor to the sofa and gets up.	10	0	100
	Night time	IV.2	Subject remains conscious, but unable to stand up for 7 minutes.	0	10	0
	Night time	IV.3	Subject experiences unconsciousness for 7 minutes.	10	0	100
Fall in shower		**V**	**Subject goes to the bathroom to shower and then falls in the shower, then:**			
	Day time	V.1	Subject is able to get up, then walks from the shower to the toilet in the bathroom.	10	0	100
	Day time	V.2	Subject remains conscious and moving, but is unable to stand up for 7 minutes.	0	10	0
	Day time	V.3	Subject experiences unconsciousness for 7 minutes.	10	0	100

4.2.2 Algorithm design

PIR activity can monitor the occupancy of a room [160], while PM activity indicates the use of furniture and movement across doorway thresholds. A fall detection algorithm processes the PIR and PM sensor data in a parallel manner. The flowchart of the proposed algorithm is shown in Figure 4.2. In this chapter, the activation or deactivation of the system is not incorporated.

The system monitors for the event where all PIR and PM sensors are OFF. If any sensors are switched ON, then it can be concluded that the subject has not fallen. However, if all sensors are switched OFF, then one of two possible situations have occurred: (1) a person experiences a fall with loss of consciousness or unable to move because of their severe injuries; or (2) a person is temporary motionless (but has not fallen) and not sitting/lying on a PM.

If all sensors are switched off for more than 5 minutes, it can be assumed that the subject is not moving and is not in bed, on a chair or any other furniture. This leads to the impression that the subject might have fallen. However, if one of the sensors reactivates within 5 minutes, it can be assumed that the subject has not fallen, but is maintaining a motionless position.

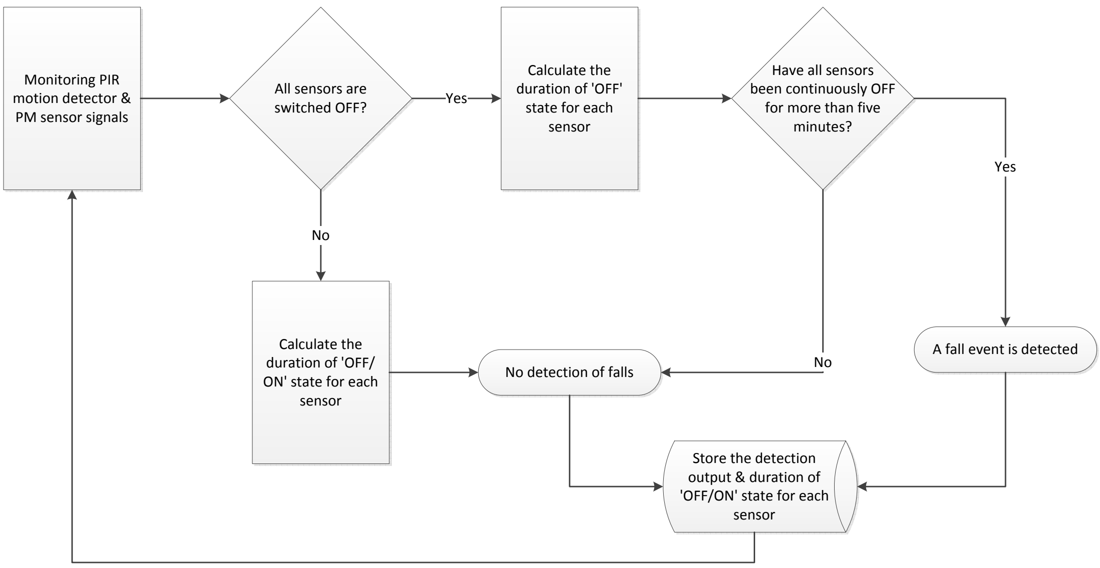


FIGURE 4.2: Shown is a diagram of the decision tree classifier employed to detect falls using the PIR and PM sensors.

The returned sensor signals, sampled at 5 Hz, the true location of all simulated agents, and the type of scenario performed, are returned by the Java-based simulation software. All further algorithm development and analysis is performed using MATLAB version 7.5 (The MathWorks, Natick, MA, USA). A copy of this MATLAB code can be found in Appendix C. List of MATLAB Code.

4.2.3 Fall detection performance

For the purposes of assessing the performance of the decision tree classifier in discriminating falls events from ADLs, four categories are considered; normal activity (N) and falls with recovery (R) are not considered as positive fall events, whereas falls with consciousness (C) or unconsciousness (U) are.

The test outcome can be positive (the falls algorithm predicting that the person experiences falls) or negative (the falls algorithm predicting that the person performs normal ADL). The test results for each person could be similar or not similar to the person's actual situation.

Four combinations were produced as follows:

- True positive: the system correctly detects the occurrence of a fall when it happens.
- False positive: the person does not actually fall, but the system detects a fall.
- True negative: the device recognises the occurrence of a normal ADL movement when it happens.
- False negative: the system reports normal activity when the person actually falls.

The evaluation method for response in these four conditions used the following criteria. Sensitivity (Sens.) [201] refers to how good a system is at correctly identifying falls. Specificity (Spec.) [201], is concerned with how good the system is at correctly classifying normal movements. Positive predictive value (PPV) refers to the ability of the system to correctly distinguish falls. Negative predictive value (NPV) refers to

		Actual value	
		p′	**n′**
Prediction outcome	**p**	True Positive (TP)	False Positive (FP)
	n	False Negative (FN)	True Negative (TN)

$$\text{PPV} = \frac{TP}{TP+FP}$$

$$\text{NPV} = \frac{TN}{FN+TN}$$

$$\text{Sens.} = \frac{TP}{TP+FN} \quad \text{Spec.} = \frac{TN}{FP+TN} \quad \text{Acc.} = \frac{TP+TN}{TP+TN+FP+FN}$$

Table 4.3: This table shows the confusion matrix and accuracy parameters respectively.

the ability of the system to correctly recognise the normal movements. The accuracy of the system refers to the number of correctly detected falls or normal activities over all different scenarios. The confusion matrix and accuracy of the system in detecting falls is presented in Table 4.3.

4.3 Results

As stated above in Section 4.2.1, the simulator produces 16 different scenarios involving one person who lives alone at home. The 16 scenarios comprise four ADLs and 12 fall events, listed in Tables 4.2. Each of these scenarios is repeated ten times, giving a total of 160 simulated scenarios.

The associated sensitivity, specificity, positive and negative predictivity, and accuracy of the fall detection system are listed in Table 4.4. The system achieved the accuracy between 80.00% and 85.71% when excluding scenarios where the subject experiences a long lie. However, when including all types of post-fall activities, the accuracy dropped to between 60.00% and 66.67%.

Table 4.4: The calculated sensitivity, specificity, positive and negative predictivity, and accuracy in classifying fall scenarios, where a true positive is considered a fall scenario which is correctly recognized.

	Number of simulated scenarios		
	Case A.1 n=60	Case B.1 n=100	Case C.1 n=160
Sensitivity	50.00	50.00	50.00
Specificity	75.00	75.00	75.00
Positive predictivity	50.00	75.00	66.67
Negative predictivity	75.00	50.00	60.00
Accuracy	66.67	60.00	62.50

(a) All scenarios are included. Case A.1 represents scenarios that were performed during the daytime (6:30 AM - 7:00 PM). Case B.1 represents scenarios that were performed during the night time (7:00 PM - 6:30 AM). Case C.1 represents scenarios that were performed during the entire day (24 hours).

	Number of simulated scenarios		
	Case A.2 n=50	Case B.2 n=70	Case C.2 n=120
Sensitivity	100.00	100.00	100.00
Specificity	75.00	75.00	75.00
Positive predictivity	50.00	75.00	66.67
Negative predictivity	100.00	100.00	100.00
Accuracy	80.00	85.71	83.33

(b) Only ADLs and falls with unconsciousness scenarios. Case A.2 represents selected scenarios that were performed during the daytime (6:30 AM - 7:00 PM). Case B.2 represents selected scenarios that were performed during the night time (7:00 PM - 6:30 AM). Case C.2 represents selected scenarios that were performed during the entire day (24 hours).

Tables 4.5-4.6 present the corresponding confusion matrices when using the system and algorithm proposed in this chapter, which has only one motion sensor at each location.

Table 4.5: Confusion matrix for simulated scenarios involving a single person living at home alone. Columns contain the true scenario simulated, while the rows contain the results estimated by the algorithm in each case. For each sub-table, there are four categories (including normal activity (N) and falls with recovery (R) are not considered as positive fall events, whereas falls with consciousness (C) or unconsciousness (U) are.)

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	10	0	0	10	PPV=50.00%
		C	0	0	0	0	
	No fall	R	0	0	10	0	NPV=75.00%
		N	0	10	0	20	
			Sens.=50.00%		Spec.=75.00%		Acc.=66.67%

(a) All scenarios that were performed during the daytime (6:30 AM - 7:00 PM) (Case A.1).

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	30	0	0	10	PPV=75.00%
		C	0	0	0	0	
	No fall	R	0	0	30	0	NPV=50.00%
		N	0	30	0	0	
			Sens.=50.00%		Spec.=75.00%		Acc.=60.00%

(b) All scenarios that were performed during the night time (7:00 PM - 6:30 AM) (Case B.1).

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	40	0	0	20	PPV=66.67%
		C	0	0	0	0	
	No fall	R	0	0	40	0	NPV=60.00%
		N	0	40	0	20	
			Sens.=50.00%		Spec.=75.00%		Acc.=62.50%

(c) All scenarios that were performed during the entire day (24 hours) (Case C.1).

Table 4.6: Confusion matrix for simulated scenarios involving a single person living at home alone. Columns contain the true scenario simulated, while the rows contain the results estimated by the algorithm in each case.

			True			
			Fall	No fall		
			U	R	N	
Estimated	Fall	U	10	0	10	PPV=50.00
	No fall	R	0	10	0	NPV=100.00
		N	0	0	20	
			Sens.=100.00%	Spec.=75.00%		Acc.=80.00%

(a) Only ADLs and falls with unconsciousness scenarios. These scenarios were performed during the daytime (6:30 AM - 7:00 PM) (Case A.2).

			True			
			Fall	No fall		
			U	R	N	
Estimated	Fall	U	30	0	10	PPV=75.00
	No fall	R	0	30	0	NPV=100.00
		N	0	0	0	
			Sens.=100.00%	Spec.=75.00%		Acc.=85.71%

(b) Only ADLs and falls with unconsciousness scenarios. These scenarios were performed during the night time (7:00 PM - 6:30 AM) (Case B.2).

			True			
			Fall	No fall		
			U	R	N	
Estimated	Fall	U	40	0	20	PPV=66.67
	No fall	R	0	40	0	NPV=100.00%
		N	0	0	20	
			Sens.=100.00%	Spec.=75.00%		Acc.=83.33%

(c) Only ADLs and falls with unconsciousness scenarios that were performed during the entire day (24 hours) (Case C.2).

4.4 Discussion

An unobtrusive system for a single person who lives alone at home has been designed, simulated and tested. The system was designed under the assumptions that the monitoring is done on a single subject living alone, and that the sensor operation is idealised. A discussion of the results is provided below:

4.4.1 Summary of results

It can be seen from Table 4.4 (Case C.1 and Case C.2) that although the percentages of specificity and positive predictive values remained the same at 75.00% and 66.67%, respectively, there was a large decrease in the sensitivity (proportion of true falls correctly detected), from 100% to 50%, and a large decrease in the negative predictivity (proportion of scenarios classified as ADLs which actually were), from 100% to 60%.

This caused a decrease in accuracy by 20.83%, from 83.33% (Case C.2) to 62.50% (Case C.1), when including scenarios where the faller remains conscious and moving, but unable to stand up for a predefined time. This indicates that the system failed to differentiate between long lie events and ADLs.

Among the six cases, the lowest and the highest accuracies, 60.00% and 85.71%, were obtained for night time activities (with and without long lie events), respectively. Even with the fact that the activities are varied during day time, the results are still promising, with classification accuracies between 66.67%-80% for day time activities (with and without long lie events).

4.4.2 Discussion of confusion matrices

From Tables 4.5(a) and 4.6(a), the system incorrectly classifies the normal activity (N) category on ten occasions, when the subject leaves the home for a long time. This condition arises because the system is continuously monitoring the environment, even though nobody is at home. In comparison, Tables 4.5(a) and 4.6(a) also show that the algorithm correctly classifies the normal activity (N) category on ten occasions, when the subject leaves the home for three minutes which is less than the threshold of five minutes.

Tables 4.5(b) and 4.6(b) contains one scenario (10 repeats) where falls with unconsciousness (U) were detected when the true activity was normal (N). These unusual scenarios involved one person sitting still while watching a movie on a portion of the living room sofa which was not covered by the PM sensor. This condition causes the "OFF" state of all sensors because neither motion nor pressure (which normally indicates use of furniture) is detected.

From Table 4.5 and 4.6, it is clear that the system incorrectly classifies a fall where the subject remains conscious and moving (C) as a normal activity (N) for every scenario simulated. This happens primarily because the system uses only one sensor to monitor the entire room and does not divide the room into upper and lower sections to identify if the movement is taking place on the floor.

4.4.3 Design considerations emerging from results

Sensor coverage

With the intention to decrease the number of false alerts, there will be two options to choose from: (1) placement of a larger PM sensor to cover the entire sofa, or bed, or chair; (2) placement of a single load sensor under the leg of a sofa or bed.

Detecting entering and leaving

The developed algorithm assumes that the subject is always in the home; however, leaving the home without deactivating the system would cause the current algorithm to infer that a fall had occurred due to the subsequent sensor inactivity. The algorithm can be improved by developing an algorithm that can be used for counting the number of persons inside the home. So that the system could be deactivated when the last person leaves the home and re-activated again when the next person enters the home.

Detecting falls without loss of consciousness

In the real situation, a fall involves an impact and is followed by a long lie. In this situation, the subject is unable to get up from the floor after falling due to broken bones, or other injuries, and remains lying down on the floor while waiting for help to arrive. If the subject did not lose consciousness, their movements will activated the motion sensor and prevent the system from detecting this abnormal situation. The algorithm can be improved by incorporating two PIR motion detectors to monitor the upper and lower halves of each room.

Time threshold

In the current system, the time threshold is set to five minutes. This threshold is guided by recommendations from Ruff et al., stating that the severity of injuries can be reduced if an unconscious subject gets help within the first 30 minutes of losing consciousness [26]. The time threshold should be long enough so that the system will not raise an alarm prematurely if the person performs normal activities in certain areas that are not monitored by the PIR and PM sensors, but will also not wait so long that their condition deteriorates.

4.5 Conclusion

An unobtrusive falls detection system has been designed for distinguishing falls from normal activities in a home with single occupancy. In this study, a series of normal and fall events, ten night time activities and six day time activities, were performed to examine the feasibility of detecting falls using a combination of ambient PIR and PM sensors.

The proposed algorithm attempts to recognise falls where the subject experiences hard falls on indoor surfaces that lead to loss of consciousness or inability to get up from the floor without assistance, due to severe injuries.

Indeed the results revealed here are less accurate when comparing them to wearable sensor solutions; for example, those presented by Lustrek et al. (an accuracy of 94.7%) [128], Al-ani et al. (a recognition rate of above 99%) [124] and Karantonis et al. (an accuracy of. 95.6%) [121]. But still, the preliminary results showed the possibility to detect falls without the need to use a body-worn device. Moreover, when the subject moves around the home at night-time, such as making a trip from the bedroom to the toilet, it is unlikely that they will remember or even feel an inclination to wear such a device [17]. Furthermore, reported accuracies from other previous studies only involved a small number of participants.

The accuracy of the system, when using a video-based solution, developed by Williams et al. [100] and Nait-Charif and McKenna [90] were 94% and 96.9%, respectively. However it must be noted that the choice to implement video-based systems poses significant challenges related to increased concerns over invasion of privacy [103], high computational complexity and/or data storage and large sensor power consumption [104], as described earlier in Chapter 2.

In the next chapter, the placement of motion sensors on the upper and lower part of the room is investigated so that the system can more correctly classify falls and long lie events, where the subject falls but remains conscious and moving. Furthermore, to minimise the number of false positive predictions, the algorithm must provide a feature to activate and deactivate the system when people enter/leave the home. Finally, to increase the robustness of the system, the WSN simulation will be expanded to deal with multiple subjects and evaluated with more complex scenarios.

Chapter 5

Simulated Unobtrusive Falls Detection with Multiple Persons

5.1 Introduction

Previous work presented in Chapter 4 has focused on developing algorithms for unobtrusive falls detection using simulated responses from passive infrared (PIR) and pressure mat (PM) sensors, aimed at older subjects living alone at home [159]. Movement (or absence of movement) in the home is detected using the PIRs and it is inferred when someone is sitting/lying down using PMs on chairs/beds, thus allowing falls to be detected by observing prolonged periods of inactivity and knowing that they are not sitting on a chair or lying on a bed.

As discussed earlier in Section 4.4, there were three obvious limitations associated with this previous simulation and the associated algorithm, which was the motivation for the work contained in this chapter. Firstly, the developed algorithm is not activated/deactivated by the system when someone enters or leaves the home; this can lead to false positive results due to the subsequent sensor inactivity. Secondly, the algorithm presented in Chapter 4 requires that there can be only one person inside the home, precluding its use in multi-person households (older people and their families). Finally, and most importantly, the system will fail to detect the long lie event if the person remains conscious and moving after they have fallen, as the sensors are continuously activated by person's movement on the floor.

To address this shortcoming the simulation has been augmented to use a vertical arrangement of two PIR motion detectors (where before there was one), with the upper motion detector inverted and also obscured using a small canopy placed below it, so that it can only monitor the upper half of the room and hence will not be activated by the movement of a fallen person. The lower motion detector is also obscured with a similar canopy placed just above it, so it only monitors the lower half of the room.

Section 5.3 describes the simulation models in detail, including the new placement of sensors, and the generated sensor data, which are used to identify how many people (or groups of people) are present, their location, and whether any of them have fallen, or whether someone has left the residence. There are one or more simulated persons in this simulation engaging in the execution of 15 different scenarios in a residential unit; namely, three scenarios of activity of daily living, and 12 different types of falls (four types of fall, each with three post-fall scenarios). Some of the scenarios in this chapter are more complex (and slightly different) from the scenarios in Chapter 4. The process of differentiating a fall from an ADL is performed using a simple heuristic decision-tree classification model.

The comparisons between an older version versus a newer version of the fall detection algorithm is presented in Section 5.4 and a detailed discussion based on the experimental data is provided in Section 5.5. Finally, in Section 5.6, the conclusions summarise the strengths and weaknesses of the system and suggest possible future work that needs to be addressed by researchers to advance the performance and realisation of this system.

5.2 Related research

To date, research for tracking subjects and distinguishing falls from ADLs, based on unobtrusive monitoring systems, usually aim to deal with one individual in the environment at any time and exclude cases that are related to long lie scenarios [170, 171] [202]-[203].

Sixsmith *et al.* [170, 171] developed a fall detection system which consisted of an array of thermal imaging sensors. Initial results indicate that only 35.7% of the actual falls with loss of consciousness are correctly recognized.

Liu *et al.* [202] utilized three PIR motion detectors which were placed at different heights on the wall. The associated sensitivity and specificity of the fall detection algorithm were 92.5% and 93.7%, respectively. Initial results are very encouraging; however, the system was only tested on four young healthy volunteers and their height was selected between 165 and 180 cm to aid the performance of the system.

Toreyin *et al.* [156] used a combination of sound signatures and PIR motion detectors to detect falls. The accuracy of the detection algorithm was 56.52% when using audio alone, and 100% when combining audio and PIR signals. However, scenarios where somebody is lying down and unable to get up off the floor after a fall were not tested in this study.

Moore *et al.* [204] mounted an array of PIR motion detectors on the wall and used two different algorithms to recognize falls. This research has demonstrated that the accuracy of fall detection algorithm varies between 75-80%. It should be noted that this system was not tested with the three types of post-fall scenario tested in this thesis, and only involved healthy volunteers performing backward and forward falls onto a large crash mat.

Xu *et al.* [203] used a chromatic optical sensor array to distinguish between a fall with unconsciousness and a person performing ADLs. This system had a sensitivity of 78.9% and specificity of 95.2%. However, it should be noted that this research has several major limitations, including only monitoring the movements of individuals in the living room with one PIR motion detector, and only attempting to identify falls with loss of consciousness.

In general, the system proposed in this chapter offers several advantages in comparison with video-based approaches, such as reduced invasion of privacy [104], lesser computational complexity, and lower power consumption by the sensors [103].

There are also significant advantages over methods which use audio sensors, such as the ability to detect falls where the impact velocity of the fall is low, generating little sound, as was observed by Zigel *et al.* for falls occurring immediately after getting up from a chair [103].

5.3 Methodology

5.3.1 Experimental design

Residential environment

The floor plan of the residential unit used in this chapter is the same as that used in Chapter 4.

Sensor placements

As described above, these PIR motion detectors are further augmented by placing two PIR motion detectors at each location, so that one detector monitors the upper half of the room and the other monitors the lower half. The two detectors are placed at 60 and 90 cm above the ground. It is envisaged that the implementation of this setup will involve the upper PIR being inverted and a semi-circular canopy, with a radius of 8 cm, is placed just below it to obscure line of sight to objects in the lower half of the room; this will assist with discriminating between fallen subjects who are conscious and moving on the floor and active subjects who continuously move in a localized area of the room. Similarly, for ease of simulation, a canopy is placed just above the lower sensor to obscure its view of the upper half of the room; it would be acceptable to remove this canopy and allow the lower sensor to monitor the entire room, but accurately simulating shadowing of the lower sensor by furniture would require moving to a fully 3-dimensional simulation.

The placement of each PM sensor remains the same as described earlier in the Chapter 4.

TABLE 5.1: Scenarios for ADLs or falls involving one person. Most of the scenarios are the same as listed in Chapter 4, although a few activities have been modified and one ADL has been removed.

Type of scenario	No.	Scenario description
ADLs	**I**	**Normal ADLs without falls**
	I.1	Subject goes from the master bedroom to the kitchen to a prepare meal. Subject sits on the dining chair and starts eating.
	I.2	Subject packs bag for work in the master bedroom and then leaves the home.
	I.3	Subject goes from the kitchen to the living room. Sits motionless on a part of the sofa that is *not* covered by a PM sensor.
Fall from bed	**II**	**In the master bedroom, subject falls from the bed to the floor (lying on the floor) near the bed, then:**
	II.1	Subject is able to get up from floor after fall, then goes from the master bedroom to the kitchen to prepare breakfast.
	II.2	Subject remains conscious and moving, but is unable to stand up for 7 minutes.
	II.3	Subject experiences unconsciousness for 7 minutes.
Fall from chair	**III**	**Subject is sitting on the dining chair. Tries to get up from the dining chair and then falls to the floor, then:**
	III.1	Subject is able to get up from floor after fall, then sits back on the dining chair.
	III.2	Subject remains conscious and moving, but unable to stand up for 7 minutes.
	III.3	Subject experiences unconsciousness for 7 minutes.
Fall when walking	**IV**	**Subject washes dishes. Subject then walks from the kitchen to the sofa in living room, falls before reaching the sofa, then:**
	IV.1	Subject then crawls along the floor to the sofa and gets up.
	IV.2	Subject remains conscious, but unable to stand up for 7 minutes.
	IV.3	Subject experiences unconsciousness for 7 minutes.
Fall in shower	**V**	**Subject goes to the bathroom to shower and then falls in the shower, then:**
	V.1	Subject is able to get up, then walks from the shower to the toilet in the bathroom.
	V.2	Subject remains conscious and moving, but is unable to stand up for 7 minutes.
	V.3	Subject experiences unconsciousness for 7 minutes.

TABLE 5.2: Scenarios with multiple persons moving about performing ADLs, and on occasion one person falls.

Type of scenario	No.	Scenario description
ADLs	**I**	**Normal ADLs without falls**
	I.1	One or two persons go from their bedroom to the kitchen to prepare breakfast. A few minutes later, another resident goes from the bedroom to the kitchen to prepare breakfast. All residents are in the kitchen for a while. They finish their meal preparation and start eating.
	I.2	One or two persons pack a bag for work in their bedroom and then leave the home. Another resident sits on the sofa and watches TV in the living room.
	I.3	One or two persons are sleeping in their bedroom. Another resident sits motionless on a part of the sofa which is *not* covered by a PM and reads a book, in the living room.
Fall from bed	**II**	**While the other person(s) sits at the dining table. One of the residents falls from the bed to the floor in the bedroom, then:**
	II.1	The faller is able to get up from floor and then goes to the kitchen to have breakfast.
	II.2	The faller remains conscious and moving, but unable to stand up for 7 minutes.
	II.3	The faller experiences unconsciousness for 7 minutes.
Fall from chair	**III**	**While the other persons(s) leaves the home after preparing themselves in their bedroom. One of the residents falls from the chair to the floor, then:**
	III.1	The faller is able to get up from floor and then sits back on the dining chair.
	III.2	The faller remains conscious and moving, but unable to stand up for 7 minutes.
	III.3	The faller remains conscious, but unable to stand up for 7 minutes.
Fall when walking	**IV**	**While the other person(s) puts clothes into the wardrobe in their bedroom, one of the residents falls before reaching the sofa, then:**
	IV.1	The faller crawls along the floor to the nearest sofa and gets up.
	IV.2	The faller remains conscious and moving, but unable to stand up for 7 minutes.
	IV.3	The faller experiences unconsciousness for 7 minutes.
Fall in shower	**V**	**While the other person(s) enters their bedroom, one of the residents falls in the shower, then:**
	V.1	The faller is able to get up from floor and then walks from the shower to the toilet in the bathroom.
	V.2	The faller remains conscious and moving, but unable to stand up for 7 minutes.
	V.3	The faller experiences unconsciousness for 7 minutes.

Resident profiles

The simulator produces a number of different scenarios, containing simple and complex scenarios with single or multiple persons (two or three persons). About half of the sample were women (468 out of 900, 52%). Age was selected randomly from a uniform distribution over the interval [45,87] years. As per Chapter 4, random BMI and height parameters are also randomly generated using a normal distribution with means and standard deviations drawn from published population statistics [200], as shown in Table 4.1. The average simulated walk speed, calculated from these ages and BMIs, is almost equal to the preferred speed of walking in normal-weight adults of both sexes, which is approximately 1.4 m/s (5 km/h) [186]. These distributions are generated using MATLAB version 7.5 (The MathWorks, Natick, MA, USA). A copy of this MATLAB code can be found in Appendix C. List of MATLAB Code.

ADL and fall scenarios

A series of predefined simulated movements were generated to simulate an older person living alone, or cohabiting with either one or two family members. In particular, ADLs, a fall from bed after waking up, a fall after getting up from a chair, and a fall when walking or standing were simulated [86].

The ADLs include walking, sitting on a sofa or chair, climbing into bed, preparing meals, showering and leaving the house. Each normal scenario can be a sequence of one or more ADLs. These scenarios aim to assess the false positive rate of the system.

For each fall event, three types of post-fall scenario are performed, including: successfully recovering, by crawling to the furniture (chair, sofa, bed) and sitting on the furniture for two minutes before trying to move again; remaining unconscious for seven minutes while on the floor; remaining conscious on the floor and moving, but unable to stand up for seven minutes.

The exact scenarios simulated are listed below in more detail in Tables 5.1 and 5.2.

5.3.2 Algorithm design

The returned sensor signals, sampled at 5 Hz, the true location of all simulated agents, and the type of scenario performed, are returned by the Java-based simulation software. All further algorithm development and analysis is performed using MATLAB version 7.5 (The MathWorks, Natick, MA, USA). The MATLAB code can be found in Appendix C. List of MATLAB Code.

Overlapping regions of sensitivity in the WSN as two undirected graphs

Later, the development of a falls detection algorithm which interprets the data returned by the motion and pressure sensors is described. It observes these sensor outputs and attempts to recognise when a fall has occurred, based on a prolonged period of inactivity while the subject is not sitting on a chair or on a bed; a version of this falls detection algorithm has been previously described in Chapter 4, but assumes that only one person is present in the environment; a second person moving in the environment when the first person has fallen will trigger the motion sensors (resetting the inactivity timer) and cause a failure to detect the fallen individual. Therefore, as a preceding algorithmic step, it must be identified which sensor activations might be attributed to which individuals (or groups of individuals) and then a variation of the existing falls detection algorithm can be applied to these subsets of sensors. The following describes how to use undirected graphs to represent the WSN, to perform this sensor subset grouping task.

The overlapping areas of sensitivity in the WSN are represented by two undirected graphs. The first graph represents the motion detectors and PM sensors monitoring the lower half of the room. The second graph represents the motion detectors monitoring the upper part of the room and again includes the PM sensors (since a lower sensor could be obscured by furniture, while an upper sensor and pressure mat may still be active). These graphs are shown overlaid in Figure 5.1(a).

For each of the two graphs representing the WSN, a vertex (or node) represents a sensor. An edge between two vertices implies that these two sensors share some physical region of overlap (no matter how small) that they are both monitoring. The utility of this representation becomes apparent when we consider two sensors which do not monitor any shared physical region. If both are activated simultaneously,

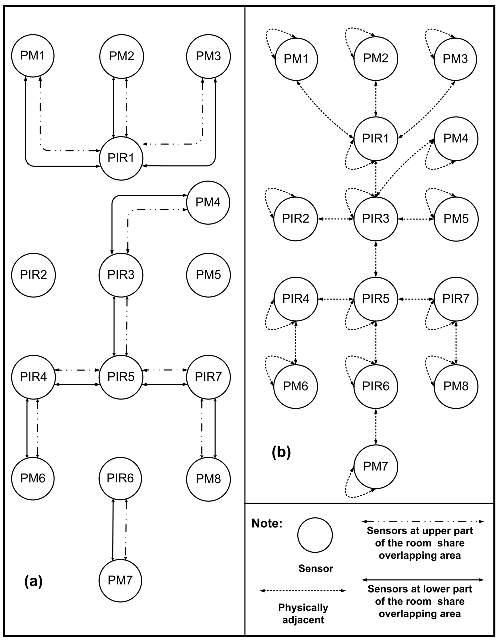


FIGURE 5.1: Regions of sensor overlap in the WSN are represented by two undirected graphs. In this figure they are overlaid on the same graph. (b) Similarly the physical adjacency of the sensors (even where they do not overlap) is represented as an undirected graph. Sensors are considered physically adjacent if an individual can sequentially activate them without needing to activate some intermediate sensor to achieve this; stated simplistically, it is possible to walk from one sensor to another without triggering a third sensor on the way.

then there must be at least two people in the environment. Thus, the challenge of identifying how many people (or physically close groups of people) are present at a fixed point in time reduces to observing the sensor activation pattern and calculating the minimum number of people required to generate such a pattern, given the connectivity of these WSN graph representations.

At some point in time, the activation patterns in the upper graph (representing detectors in the upper part of the room and PM sensors) and lower graph (representing detectors in the lower part of the room, and also the same PM sensors) are simplified by removing all vertices (and associated edges) representing sensors which are not currently activated.

After inactive sensors and associated edges have been removed from the graph, independently for each (upper or lower) graph the minimum number of people required to generate such an activation pattern is estimated by repeating the following process. The maximum clique in the graph is found using the Bron-Kerbosch algorithm

[205]; the maximum clique is the largest subset of nodes for which every node is connected to every other node in the subset by an edge. This subset of nodes is removed from the graph and the maximum clique for the remaining subgraphs is again found. This process is repeated until all nodes in the original graph have been assigned to cliques. Each iteration identifies the presence of another individual in the environment, as the sensors in each clique could all be activated by a single person, since they all share a region of overlap with every other sensor in the clique.

Once the graph has been subdivided into cliques, the cliques in the upper and lower graphs must be reconciled, based on the knowledge that (by design) two PIR motion detectors are present at each location, illustrated in Figure 5.2. Sequentially, in no particular order, cliques in the upper and lower graphs which share at least one node are combined into a single sensor set. These cliques are then removed from the pool and the process repeated until all cliques from upper and lower graphs have been combined. It can happen that a clique in the lower graph is not combined with any cliques in the upper graph, due to someone moving on the floor after falling (activating a lower sensor) and the corresponding upper sensors being inactive. Similarly, a clique in the upper graph may not combine with any clique on the lower graph, if the lower sensors are obscured by furniture and hence remain inactive.

The previous section has described how, at a fixed point in time, the sensor activation profile can be examined to determine the minimum number of people present in the environment. The following sections detail how temporal information is used to reconcile cliques across time steps and hence track individuals over time.

Pairing, merging and splitting cliques for tracking

The previous section described how to analyze a snapshot of sensor activation at a single time point to determine how many individuals (or groups) are present in the residence at that time, and their approximate location. When these individuals are moving the problem becomes more challenging, as individuals may move in groups and then split up and move in separate directions as individuals, or move alone and then merge into a group. As cliques will merge or split, or simply change as a person moves (and activates different sensors), cliques identified at successive time steps must be reconciled to enable robust tracking of subjects. To achieve this some

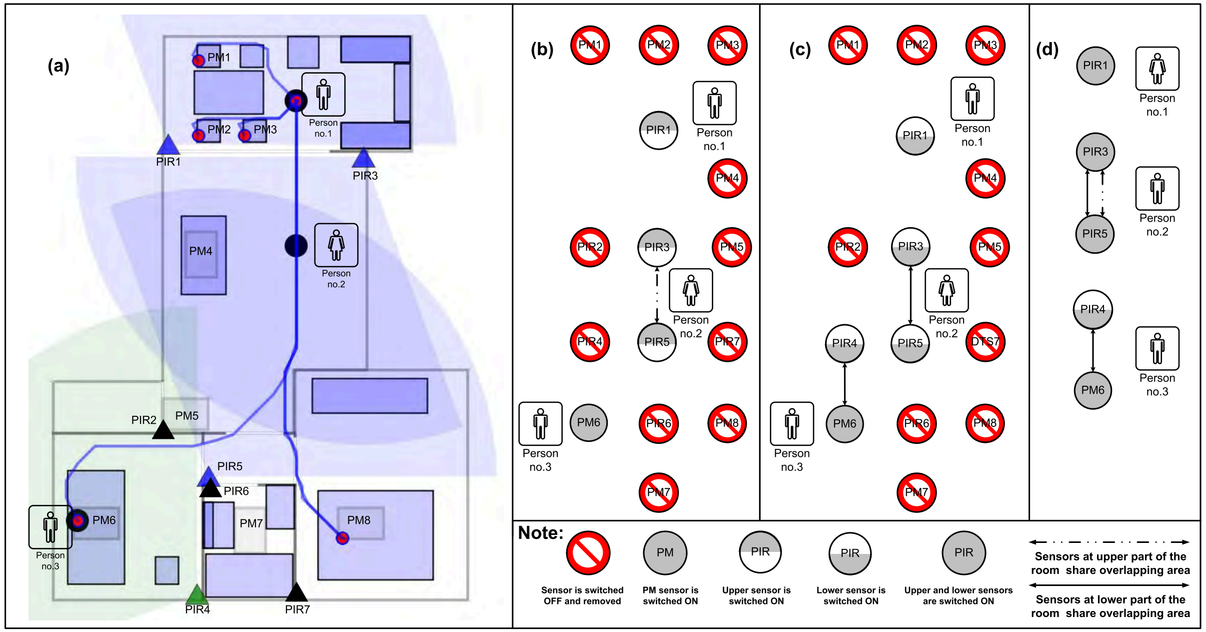


FIGURE 5.2: (a) The WSN simulator simulates multiple persons moving about performing ADLs. Given a scenario, in the form of a list of locations which must be visited in order, or tasks which must be performed, their trajectory through the environment is plotted using the A* pathfinding algorithm. The responses of the PIR motion detectors and the PM sensors are also simulated, being triggered when the simulated persons (shown as bold circles in the graphic) interact with their regions of sensitivity. In the graphic, the triangles represent the PIR motion detectors and the PM sensors are also shown as labeled rectangles. The sensitive regions of the sensors being triggered by movement at this point in time are highlighted. (b) The maximum cliques in the upper graph are determined, after edges associated with inactive sensors are removed (see Fig. 5.1(a) for complete unaltered graph). (c) Similarly, the maximum cliques in the lower graph are determined. (d) Finally, the cliques from the upper and lower graphs are merged to identify the number of people/groups in the residential unit and which sensor subgroups are activated by them at this point in time.

representation of the physical layout of the sensors and the environment is required; this is addressed in the next section.

Physical adjacency graph The physical adjacency of the sensors (even where they do not overlap) can also be represented as an undirected graph. Sensors are considered physically adjacent if a subject can sequentially activate each sensor without needing to activate some intermediate sensor to achieve this; stated simplistically, it is possible to walk from one sensor to another without triggering a third sensor on the way. The physical adjacency graph for the simulated environment can be seen in Figure 5.1(b). This is an important concept, as some WSN sensors may not contain any overlap of sensitive areas, and hence it would become impossible to track individuals using the graph which quantifies sensor overlap, as described earlier.

The following sections describe how the physical adjacency graph is used to reconcile cliques over time.

Pairing In the simplest case, the number of cliques at successive time points will be the same. If at time $t = t0$ there are N cliques (people) (each of these cliques is a list of sensors that all share overlaps in their sensitive region), then at time $t = t1$ there are also N cliques, but the list of sensors in each of these latter cliques might be slightly different (as the person is moving), the task is to pair the cliques from $t = t0$ with those at $t = t1$ so movement can be tracked. The physical adjacency graph, described above, allows a decision to be made as to which cliques should be paired. This is achieved by using a metric, to compare the similarity between cliques at successive time points, which counts the total number of edges which must be traversed in the physical adjacency graph from each node in the clique at $t = t0$ to reach the nearest node in the candidate clique at $t = t1$. The most similar cliques at successive time points are paired.

Splitting If there is an additional clique identified at $t = t1$ than existed at $t = t0$, the parent clique at $t = t0$ is found by examining the physical adjacency graph to see from which clique at $t = t0$ the new clique mostly likely emerged. In addition, at least one node in the selected parent clique must be connected to at least one node in the newly formed clique.

The additional cliques are compared to the selected parent cliques and a similarity score is found for each comparison. These similarity scores are then numerically ranked in descending order. The correct match is decided based on the highest similarity score.

Merging, leaving or falling? If the number of cliques at the $t = t1$ is less than at $t = t0$, the system attempts to find the cliques at $t = t0$ which can be merged and then subsequently paired with a clique at $t = t1$. First, the cliques at $t = t0$ are paired with those from $t = t1$ in a one-to-one pairing. The remaining unpaired cliques from $t = t0$ are merged into those at $t = t1$ using the same metric of similarity used when pairing, derived from the physical adjacency graph (described above). However, when merging, each node in the clique at $t = t0$ must be physically adjacent to at least one node for the candidate clique at $t = t1$.

If, by these criteria, it is not possible to merge an unpaired clique from time $t = t0$ with any from $t = t1$, then one of three possible situations have occurred: (1) a person has left the residence; (2) a person is motionless (but has not fallen) and not sitting/lying on a PM, or; (3) a person has fallen and is unconscious and hence motionless.

If the unpaired clique includes the PIR motion detector at the entrance of the residence, it is assumed that a person has left the building and monitoring stops for that person and the clique is dropped, rather than merged, at $t = t1$.

If it is deemed that nobody has left the residence, the unpaired clique is placed on a 'watchlist'. If another clique moves within proximity (activating one of the sensors of that clique) or one of the clique sensors reactivates within 20 seconds, it is concluded that the person was temporarily motionless but has now joined with the passing person (or group) or has started moving again, and the cliques are merged and the unpaired clique taken off the watchlist.

However, if more than 180 seconds have elapsed and the clique is not absorbed by a passing clique that comes within proximity, and none of the sensors in the clique are reactivated, it is concluded that the person remains motionless and may have fallen and lost consciousness. In this case, monitoring of the sensors signals in the clique continues using the fall detection decision tree described below.

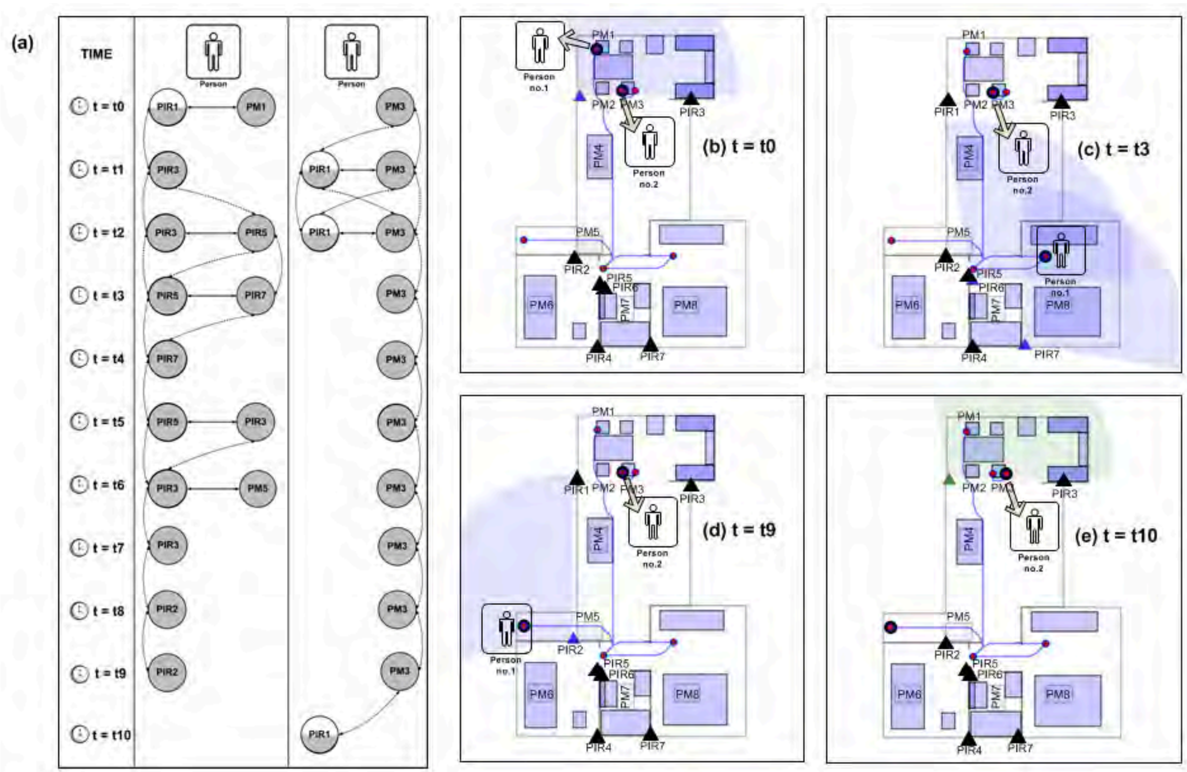


FIGURE 5.3: (a) An illustrative example of the process of tracking multiple persons. At each time point, the number of cliques identified and the active sensors which they constitute are shown. (b) Snapshot of the plan view at time $t = t0$. All two are having breakfast together. (c) Snapshot of the plan view at time $t = t3$. Person no. 1 is going to the bedroom to prepare themselves. (d) Snapshot of the plan view at time $t = t9$. Person no.1 leaves the home. (e) Time $t = t10$. Person no.2 falls from the chair to the floor, remains conscious and moving, but unable to stand up. Note: Refer to the same legend in Figures 5.1 and 5.2.

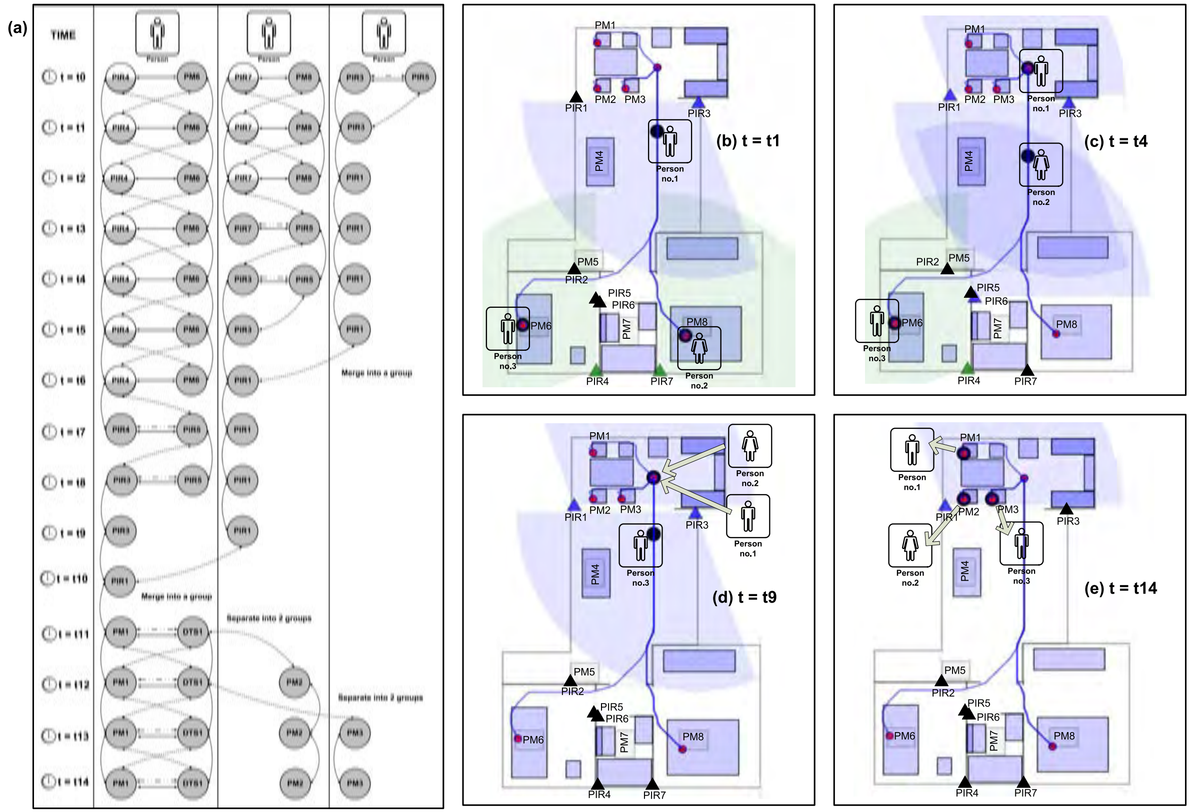


FIGURE 5.4: (a) An illustrative example of the process of tracking multiple persons. At each time point, the number of cliques identified and the active sensors which they constitute are shown. Also shown is the merging and splitting of groups as the number of cliques changes between successive time points. The overlapping areas between sensors will clearly impact sensor selection for each individual. As a result, there will be several cross-overs in the merging and splitting processes. (b) Snapshot of the plan view at time $t = t1$. Person no. 1 is going to the kitchen to prepare breakfast while others are sleeping in bed. (c) Snapshot of the plan view at time $t = t4$. Person no. 2 is going to the kitchen to prepare breakfast, following person no.1, while person no.3 is sleeping in bed. (d) Snapshot of the plan view at time $t = t9$. Person no. 3 follows the others to the kitchen. (e) Time $t = t14$. All three are having breakfast together. Note: Refer to the same legend in Figures 5.1 and 5.2.

Figure 5.4 contains an illustrative example of pairing, splitting, and merging of cliques for three people walking through the residential environment as they move to the kitchen to dine.

Fall detection

Once the sensor activation pattern has been spatially segmented into cliques to identify how many people are present in the environment and for which sensor activations they are responsible, an augmented version of the fall detection algorithm from Chapter 4 is independently applied to each of the sensor subsets within each clique. As described earlier, this existing algorithm waits until a time threshold of movement inactivity has been exceeded, while ensuring the subject is not sitting in a chair or lying on a bed. The algorithm has been altered to utilise the information provided by the independent monitoring of both the upper and lower halves of the room by using two time threshold parameters when activity is seen on the lower sensors only; activity on the lower sensors only may imply that the subject has fallen but now remains conscious and moving but unable to get up. The algorithm uses the following rule set:

Fall with unconsciousness For each identified clique (including cliques which may have been placed on the watchlist earlier) check the following:

- Have all upper PIR motion detectors in the clique been continuously off for more than five minutes?
- Has each of the lower PIR motion detectors in the clique been (cumulatively) on for less than five minutes? (Intermittent movement is allowed.)
- Have all PM sensors in the clique been continuously off for more than five minutes?

If all of these conditions are true, it is deemed that the subject has fallen and has remained quite still and is possibly unconscious.

Fall with consciousness and intermittent movement Similarly, to decide if a person may have fallen but is possibly still conscious and moving, check the following:

- Have all upper PIR motion detectors in the clique been continuously off for more than five minutes?
- Has each of the lower PIR motion detectors in the clique been (cumulatively) off for less than three minutes? (Intermittent inactivity is allowed.)
- Have all PM sensors in the clique been continuously off for more than five minutes?

If all of these conditions are true, it is deemed that the subject has fallen but is possibly still conscious and appears to be moving.

5.3.3 Fall detection performance

For the purposes of assessing the performance of the above decision tree classifier in discriminating falls events from ADLs, four categories are considered: normal activity (N) and falls with recovery (R) are not considered as positive fall events, whereas falls with consciousness (C) or unconsciousness (U) are. Confusion matrices showing the comparison results are listed in section 5.4 below.

The performance is also compared to the performance of an algorithm previously described in Chapter 4. As outlined earlier, the previous algorithm uses a single motion sensor at each location and does not incorporate any graph theory concepts to improve multiple persons scenario results. The latest algorithm in this chapter uses two motion sensors at each location (which monitor the upper and lower halves of the room and does incorporate graph theory concepts. This graph representation enables the tracking of multiple subjects/groups within the environment, by analysing the sensor activation and adjacency profiles, hence allowing individuals/groups to be isolated when multiple persons are present, and subsequently monitored for falls events.

5.4 Results

As stated above in section 5.3, the simulator produces 45 different scenarios; i.e., 15 scenarios each for either one, two or three persons inside the home. The 15 scenarios comprise three ADLs and 12 fall events, listed in Tables 5.1 and 5.2. Each of these scenarios is repeated ten times, giving a total of 450 simulated scenarios.

Table 5.3(a) lists the associated sensitivity, specificity, positive and negative predictivity, and accuracy of the fall detection system when using the system proposed here, compared to the basic system and algorithm of Chapter 4, in Table 5.3(b). The results in Table 5.3(a) show an accuracy of 93.33% for scenarios with one person, decreasing to 87.33% for scenarios with two and three people, when using the new

Table 5.3: The calculated sensitivity, specificity, positive and negative predictivity, and accuracy in classifying fall scenarios, for two different systems, where a true positive is considered a fall scenario which is correctly recognized.

(a) Falls detection performance using the system and algorithm proposed in this chapter, which uses two PIR motion detectors to monitor the upper and lower halves of each room, combined with an augmented algorithm which uses graph theory to infer subject locations from sensor activation patterns. Each of 15 scenarios from Table 5.1 (for one person) and Table 5.2 (for two and three people) are repeated 10 times, giving 150 simulated scenarios for each number of people.

	Number of residents			Total
	One person n=150	Two persons n=150	Three persons n=150	n=450
Sensitivity	100.00	100.00	100.00	100.00
Specificity	85.71	72.86	72.86	77.14
Positive predictivity	88.89	80.81	80.81	83.33
Negative predictivity	100.00	100.00	100.00	100.00
Accuracy	93.33	87.33	87.33	89.33

(b) Similarly, this table presents the falls detection performance using the system from Chapter 4, which uses only one motion detector at each location, making it unable to distinguish between activity in the upper and lower parts of the room. This algorithm does not use any graphical representation of the environment to improve detection performance. Note, two positive predictive values are undefined (NaN) as no falls were correctly detected; see Table 5.5(b) and (c) for detailed results.

	Number of residents			Total
	One person n=150	Two persons n=150	Three persons n=150	n=450
Sensitivity	50.00	0.00	0.00	16.67
Specificity	85.71	100.00	100.00	95.24
Positive predictivity	80.00	NaN	NaN	83.33
Negative predictivity	60.00	46.67	46.67	50.00
Accuracy	66.67	46.67	46.67	53.33

system and algorithm. In contrast, Table 5.3(b) shows results for using only one motion detector at each location and no graphical interpretation of the sensor activations (the algorithm from Chapter 4), resulting with 66.7% accuracy for scenarios with one person, dropping to 46.67% for two or three persons.

Table 5.4 presents the corresponding confusion matrices when using the system and algorithm proposed in this chapter (that is, sensors monitoring the upper and lower parts of the room, and using a graph theoretical framework to interpret activity).

TABLE 5.4: Confusion matrix for fall classification using two PIR motion detectors at each location to monitor motion in the upper and lower parts of the room. For each sub-table, there are 15 scenarios (including three normal ADLs (N), four falls followed by recovery (R), which are not considered as positive fall events, four falls with consciousness (C) and four falls with unconsciousness (U). Each of these scenarios are repeated ten times. Columns contain the true scenario simulated, while the rows contain the results estimated by the algorithm in each case.

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	40	0	0	10	PPV=88.89%
		C	0	40	0	0	
	No fall	R	0	0	40	0	NPV=100.00%
		N	0	0	0	20	
			Sens.=100.00%		Spec.=85.71%		Acc.=93.33%

(A) Confusion matrix for one person in the residence.

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	40	8	9	10	PPV=80.81%
		C	0	32	0	0	
	No fall	R	0	0	31	0	NPV=100.00%
		N	0	0	0	20	
			Sens.=100.00%		Spec.=72.86%		Acc.=87.33%

(B) Confusion matrix for simulated scenarios involving an older person cohabiting with one family member.

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	40	6	9	10	PPV=80.81%
		C	0	34	0	0	
	No fall	R	0	0	31	0	NPV=100.00%
		N	0	0	0	20	
			Sens.=100.00%		Spec.=72.86%		Acc.=87.33%

(C) Confusion matrix for simulated scenarios for an older person cohabiting with two family members.

In comparison, Table 5.5 lists the confusion matrices resulting when four different categories of falls and ADLs are estimated (N, R, C and U), using the older algorithm of Chapter 4, which has only one motion sensor at each location and thus cannot distinguish between the upper and lower parts of the room, and cannot group sensor activations according to the locations of different people or groups.

Table 5.5: Confusion matrix for fall classification using the older system and algorithm of Chapter 4. Again, for each sub-table, there are 15 scenarios (including three normal ADLs (N), four falls followed by recovery (R), which are not considered as positive fall events, four falls with consciousness (C) and four falls with unconsciousness (U). Each of these scenarios is repeated ten times. Columns contain the true scenario simulated, while the rows contain the results estimated by the algorithm in each case.

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	40	0	0	10	PPV=80.00%
		C	0	0	0	0	
	No fall	R	0	0	40	0	NPV=60.00%
		N	0	40	0	20	
			Sens.=50.00%		Spec.=85.71%		Acc.=66.67%

(a) Confusion matrix for one person in the residence.

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	0	0	0	0	PPV=NaN
		C	0	0	0	0	
	No fall	R	0	0	40	0	NPV=46.67%
		N	40	40	0	30	
			Sens.=0.00%		Spec.=100.00%		Acc.=46.67%

(b) Confusion matrix for simulated scenarios involving an older person cohabiting with one family member.

			True				
			Fall		No fall		
			U	C	R	N	
Estimated	Fall	U	0	0	0	0	PPV=NaN
		C	0	0	0	0	
	No fall	R	0	0	40	0	NPV=46.67%
		N	40	40	0	30	
			Sens.=0.00%		Spec.=100.00%		Acc.=46.67%

(c) Confusion matrix for simulated scenarios for an older person cohabiting with two family members.

5.5 Discussion

An unobtrusive fall detection system has been designed, simulated and tested. The system can operate with multiple people moving in the residence. The system monitors each individual in the home environment and attempts to recognise falls where the subject is unable to recover without help. In particular, normal ADLs (N) and three types of fall scenario are simulated; the three types of falls include a fall followed by recovery (R), a fall where the subject cannot get up but remains conscious and moving (C), and a fall where the subject is rendered unconscious (U). Each of these types of scenarios are simulated with either one, two or three people in the residence at any one time (but only one person ever falls), and repeated ten times, giving a total of 450 simulated scenarios. The results relating to these scenarios are discussed below.

5.5.1 Summary of results

From Table 5.3(a) and (b), the overall accuracy of the new system and algorithm is superior to that of the more naive system and algorithm of Chapter 4, giving a total accuracy of 89.33% versus 53.33%, respectively.

In particular, the improvement in accuracy is obtained from an increase in sensitivity (proportion of true falls correctly detected), rising from 16.67% to 100%, and an increase in negative predictivity (proportion of scenarios classified as ADLs which actually were), up from 50% to 100%.

Positive predictivity (proportion of scenarios classified as a fall where a fall actually happened) remains the same, at 83.33%. However, there was a small decrease in the specificity (proportion of true ADLs correctly identified), from 95.24% to 77.14%. This indicates that more ADLs are being misclassified as falls. A more detailed breakdown of these results is outlined below.

5.5.2 Discussion of confusion matrices

From Table 5.5(a), (b) and (c), it is clear that the older system incorrectly identifies a fall where the subject remains conscious and moving (C) as a normal activity (N) for every scenario simulated. This happens primarily because the older system cannot distinguish between the upper and lower parts of the room. From Table 5.4 it is seen that almost all of these falls are correctly detected when the new system is used, which has independent sensors monitoring the upper and lower parts of the room.

Table 5.4(b) and (c) also contains two scenarios where a fall with consciousness (C) and a fall with recovery (R) were misclassified as a fall with unconsciousness (U). These unusual scenarios involved one person falling and then either remaining conscious or recovering, in a location which was monitored by the same sensor which monitors the front door. This fall happens just as the second person leaves the residence. Thus, the system fails to recognise that someone has left the residence and determines that two types of fall have occurred (inferring that the person who left is now unconscious). Here U takes priority over C or R, causing a misclassification. If it was known that a person had left the residence, these errors would not have occurred.

From Table 5.5(b) and (c), the older system incorrectly classifies all falls where the subject experiences loss of consciousness (U) as a normal activity (N), when there are others in the home. This condition arises due to other people moving in the environment causing some sensors to activate. Since this algorithm is ignorant to the sensor locations and their overlap, such falls cannot be detected once this activation happens. In comparison, Table 5.4 shows that the new algorithm correctly classifies all falls with unconsciousness (U), even when there are other people in the home, by using the graphical representation of the sensor network and environment to group sensor activations and assign them to individuals.

There is a scenario of interest, I.3 from Tables 5.1 and 5.2, common to both one person and multiple persons simulations. This scenario involves a portion of the living room sofa having no PM sensor covering it. In the one person scenario, when the person sits still in this position (reading a book) so that no motion detectors are activated, a fall with unconsciousness is detected (U) when the true activity is normal (N). Ironically, this is corrected by the old algorithm for the multiple persons scenario because there are other people in the environment causing sensors to activate (see Table 5.5(b) and (c)). However, this error persists with the new system (see Table 5.4(b) and (c)), highlighting the need for the environment to be comprehensively covered.

5.5.3 Design considerations emerging from results

Sensor coverage

If an area is not comprehensively monitored, an individual may move into a blind spot and appear to have fallen and lost consciousness. It is feasible to get close to full coverage using PIR motion detectors, however, fully instrumenting every bed and chair in the residence is somewhat more onerous. As stated earlier in Chapter 4, it may be more practical to use load sensors, rather than PM sensors, such that a single sensor might be placed under the leg of a sofa or bed and the number of persons present detected by the changes in load sensed.

Indeed it is unlikely that real sensors will match the ideal performance of the sensors simulated here. It is important to first understand how such an algorithm will perform with idealised sensor performance before the degradation of this algorithm in the face of realistic sub-optimal sensor performance is investigated. While we are unaware of any research which has characterized the proposed sensors, we will proceed a characterisation work in the future with the intention to repeat the simulation with more realistic sensor models.

Detecting entering and leaving

If it is known how many people are present in the residence at any one time then the system appears to perform well. Future embodiments of this system will consider more robust means of detecting when someone enters or leaves the building.

Time thresholds

The threshold values chosen here are somewhat arbitrary. However, they are guided by recommendations from Ruff et al., stating that the severity of injuries can be reduced if help can be delivered to the person who is unconscious within approximately 30 minutes [26]. The choice of a longer threshold, to detect a fall where the subject remains unconscious on the floor, should be long enough so that if the person has not fallen, but is sitting or kneeling motionless on the floor, the system will not raise an alarm prematurely, but will also not wait so long that their condition deteriorates.

5.6 Conclusion

This WSN simulation is an important phase in the development and testing of the proposed unobtrusive fall detection system, before hardware prototyping. Both simple and complex scenarios have been examined to verify the feasibility and identify flaws in the system.

The WSN simulator generates signals from motion detectors and PM sensors, triggered by simulated people moving around the residence. Fall detection results indicate that a higher detection sensitivity can be achieved by using independent motion sensors to monitor the upper and lower parts of the room, allowing the detection of falls with unconsciousness. In addition, the use of graphical representations of the sensor locations and their shared regions of overlap allow sensor activation, caused by multiple persons in the environment, to be grouped, enabling falls with unconsciousness to be detected in remote parts of the environment.

The remaining weaknesses of the system include false alarms occurring when someone moves into a part of the residence not monitored by any sensors, or when the system fails to detect that someone has left the building.

Future work will focus on hardware prototype fabrication and then deriving preliminary implementation falls detection system in either laboratory or real-world environments.

It is hoped that unobtrusive technologies, like that described here, will become part of the modern home in the future and help older people live at home for longer with a lessened fear of falling.

Chapter 6

Conclusion

6.1 Introductions

This chapter presents the conclusion of all the work that has been accomplished in this doctoral research, namely the development of simulator tools and algorithms that are designed to track the movement of multiple persons and to unobtrusively detect falls when they occur, therefore reducing the rate of occurrence of long lie scenarios. The performance of the fall detection algorithm were analysed, based on data generated by way of simulation. The overall structure of the thesis consisted of four main parts.

The first part focused on developing tools to generate simulated signals with known characteristics. These tools could be divided into two main software modules. The first software module was a computer-aided design (CAD) tool developed for drafting the layout of the floor plan and the allocation of ambient sensors. The second software module was a simulator for simulating and visualising the movements of people and the response of sensors placed in a mock residential environment. In addition, the intended use of this software was to generate sensor signals which may be considered as mimicking the real sensor signals of a subject performing certain activities.

The second part focused on the development of an algorithm to distinguish between falls and other activities during the nighttime in a house where only one elderly person lived. The algorithm was used to classify normal activity patterns and to detect falls events based on the pattern of sensor activity. The algorithm assumed that the person may have fallen and lost consciousness if neither motion sensors nor pressure mat sensors detect human movement for five minutes.

The third part focused on the algorithm development for recognising three post-fall events (successfully recovering, and falls with and without loss of consciousness) and daily activities in the presence of multiple persons around the house during the day. This algorithm worked in two main phases: tracking the movement of people in indoor environments and applying the fall detection algorithm to each individual.

Overall the results demonstrated the importance of using simulator software for testing fall detection algorithm performance, prior to hardware prototyping and real world testing. The main contributions of this doctoral research are presented in the following section.

6.2 Major contributions

The contributions of this thesis are:

Chapter 3

- In this chapter, software was developed to allow the researcher to reduce their reliance on costly and time-consuming hardware prototyping.
- The map editor provided the capability of creating and manipulating the layout of a residence with ease.
- The simulator provided the capability of modeling and simulating the responses of sensors to either daily activities and/or fall events. It also generated the needed signals for fall detection algorithm development purposes.

Chapter 4

- This chapter contributed an understanding of how uncovered areas in the sensor network could decrease the system performance. This is because a system misclassified daily activities as falls when those activities took part in an area that was not covered by sensors.
- In this chapter, a fall resulting in unconsciousness was detected by the system when either motion sensors or pressure sensors were switched off for more than five minutes.
- The work in this chapter leads to an understanding that there are three issues that need to be addressed in the next chapter. Firstly, the system is not activated/deactivated when a subject enters or leaves the home; this would cause the proposed algorithm to infer that a fall with loss of consciousness had occurred due to the subsequent sensor inactivity. Secondly, the algorithm assumes that a person living at home alone, hence precluding its use in larger residential care environments containing multiple agents (residents and carers). Finally, and most importantly, if the person falls without loss of consciousness and is moving on the floor then the system will categorise that as a non-fall category, as the movements on the floor are continuously detected by the sensors.

Chapter 5

- The novelty of the work contained in this chapter is the use of the simulated wireless ambient sensors (motion detectors and pressure mat sensors) to track the movement of multiple persons for unobtrusive fall detection.
- The key tracking method made novel use of graph theoretical concepts to track each individual in the residence and to monitor them independently for falls.
- The novelties of the developed expanded fall detection algorithm are the capability of identifying long lie scenarios, detecting unconscious falls on the floor in the presence of multiple persons and classifying successful recovery after falls as daily activities. The algorithm performed this analysis based on the

sensor's response at lower and upper parts of the room. The long lie event could be recognised by the system when only sensors monitoring the lower part of room responded to movement of the fallen but conscious individual, while unconscious falls could be identified by the system when all sensors in the room were deactivated

- The research conducted has also demonstrated the importance of activation and deactivation when residents enter or leave the house to avoid system errors and reduced performance.

6.3 Future directions

Several directions of future work for extending this thesis are presented below.

6.3.1 Sensor characterisation

A typical PIR sensor is sensitive to rapid change in the amount of incident infrared energy, so their response is affected by various factors including: the ambient temperature, humidity, the speed of motions, the orientations of motions, the distance between the sensor and moving objects, the size of moving object [182].

Kaushik et al. noted that the PIR sensor will remain OFF, or generates signals of very short duration, when the distance between the sensor and the moving object increases significantly [206]. Moreover, the study also found that the orientation of the moving object could cause a difference in results. These motion sensors are less sensitive to movement directly towards/away from them and require movement of the person across the detection zone to obtain a higher sensitivity.

There is another drawback of using a classical PIR sensor, since it responds to any warm objects that emit a reasonable amount of infrared radiation including humans, animals or even movement of warm air. This situation could lead to false alarms because the sensor does not have the ability to differentiate between humans or animals [156]. In other words, conclusions cannot definitively be drawn as to what kind of object is moving around in the environment from the digital output signals of the PIR sensors.

The aim of a future laboratory trial (beyond the scope of this thesis) is to gain knowledge about a PIR sensor (in this case manufactured by Matsushita Electric Works Ltd) so that the real signal characteristics can be fed into simulation tools with the intention of improving the robustness of the fall detection system.

Each ambient sensor will consist of either a motion detector or a pressure sensor. Data acquisition will be performed using a Texas Instruments MSP430 low power microcontroller. The device will be powered by an AC adapter and data retrieval will be performed using a compact low power WiFi module (G2 Microsystems, Sydney, Australia).

As described in Chapter 5, the upper motion detector is inverted and a semi-circular canopy, with a radius of 8 cm, is placed just below it to obscure line of sight to objects in the lower half of the room, so that it can discriminate between fallen subjects who are conscious and moving on the floor and active subjects who continuously move in a localised area of the room. In order to allow the lower sensor to monitor the entire room, the canopy is removed from the lower detector.

6.3.2 Implementation of a fall detection system

A possible future trial implementation could involve the following considerations. The location of the trial would be in a home unit. The home unit would be instrumented with up to a dozen environmental sensors and video cameras. The data from these tools would be acquired using a radio link and recorded and stored automatically in a database.

The trial would involve a number of subjects performing the following activities: normal activities of daily living, a fall from bed after waking up from a sleep, a fall after getting up from a chair, a fall when walking or standing, as well as a number of other postulated likely scenarios; e.g., transition events involving a person moving from the bedroom to the bathroom and falling in the bathroom. For each fall scenario, the subject would perform three types of post-fall scenarios, including successfully recovering; remaining on the ground mimicking incapacitation or unconsciousness for several minutes; and conscious but unable to stand up for several minutes. The subject would also perform a series of activities of daily living, such as sitting on a sofa or chair, climbing into bed, preparing meals, standing under a shower and leaving the house.

6.4 Conclusions

In conclusion, as more and more older people live longer, quality of life and safety become important issues, not only to them and their families, but also to government and taxpayers who are funding the health services.

Quality of life is a difficult concept to quantify since it involves lifestyle issues as much as health issues. There has been an increase in life expectancy in many countries in recent years. Older people prefer to live as independently as they can in their own home. However, there are many challenges and risks associated with independent lifestyles; for instance, falls and their related injuries.

One proposed solution to address the specific issue of older people falling at home is a system that monitors the daily activities of subjects and detects a fall without the need to use camera devices or wearable sensors. The system must be robust enough to perform automated fall detection in either single occupancy or multiple occupancy residences

This research describes one incremental step in this task and will benefit work in this area in future theoretical and implementation stages. A key role in the future of this field is to transfer the outcomes from this research into a real unobtrusive fall detection system that can offer comfort and safety for older people and their families within their own living environment in the event of an emergency.

Appendix A. Map Editor

As mentioned earlier in Section 3.3, the map editor is a software tool that allows the researcher to manually draw a floor plan or a map of the home, and also show the sensors' locations and orientations, of which the WSN consists. Map editor has a module called "bsl.mapeditor.mapEngine". This module contains seven main packages and a total of 30 classes. Each class is briefly described but only one class is documented in detail, as a representative example. The reason why the author only gives the summary of the class in this appendix is because there are too many lines of code and the appendix would be too long, and the additional inclusion of these classes would not contribute significantly to the document.

Package bsl.mapeditor.GridHandler.data

AbstractTile A tile can contain a number of information, including: 1) Multiple sensor coverage; 2) If a physical object is on it. This may include furniture, wall, person, door and opening; 3) If a tile is set to a wall, it can have a person or furniture, there is other combinations of physical objects that can be defined; and 4) Movement value, an value for path finding algorithm specifying the cost of moving across this tile. An abstract tile contains all these information, it does not set out the dimension or shape of the tile.

grid 1) Maintains the data structure of the tile of the grid. The is generated by : a) Extracting the object information from the SVG Map (i.e. walls, doors, sensors). b) Extract the SVG coordinate information of the objects from the SVG Map; 2) The grid dimensions are constructed based on the SVG coordinates, the map Engine API should contain the scaling information of the Grid. a) The grid size is initialised based on the min and max x,y value of the SVG Map; and b) The SVG Objects are inserted into the grid.

TileMovement Implies movement along a compass direction.

TileSensorProperty This class is used by a tile to describe the sensor location and the meta-data information with regard to the sensor and this particular tile i.e. the probability of this sensor being triggered at this tile.

Package bsl.mapeditor.GridHandler

Grid API Generate grid from SVG Map. Set grid size. Extract specific tile based on SVG coordinate. Check tile information. Set tile information for dynamic scenarios. Keep track of which tile belong to which object.

Package bsl.mapeditor.mapEngine

MapCanvas Extend from JSVGCanvas, this canvas is for visualisation of SVG document.

MapEngineAPI Contains and reference all data structures of the map ui components and associated high level methods. Contains: VisHandler and SvgHandler. Visualisation Handler controls the visualisation aspect, i.e. how SVG elements are displayed during insertion, selection etc. Once Visualisation Handler finishes the visualisation, the SVG element can than be inserted into the SVG document using the SVG handler. The SVG Handler controls the SVG related document API and the SVG data structure. This class is a singleton.

Package bsl.mapeditor.mapEngine.svg.components

AbstractRoom This is a base class to represent a room object.

DoorObject This class provides methods for a door object.

Furniture Class to represent Furniture object.

Mapobject An map object represents an SVG illustration of a component on the map. The implementing class may contain more meta-data information with regard to this object The purpose of this object is to provide an easier mean to identify what the SVG Element represents and also simplify the creation of a SVG Element (i.e. the initial coordinates before it is written into XML format).

PIR This class provides methods for a PIR sensor object. pt1 - position pt2 - orientation.

PM This class represent pressure mat sensor object.

PolygonRoom This class provides methods for a polygon room object.

RectangularRoom This class provides methods for a rectangular room object.

Sensor Abstract class of sensor.

Package bsl.mapeditor.mapEngine.svg

InsertObj Enumeration of SVG shape objects.

prefix obj Enumeration of WSN map prefix definitions.

SVGAttributes SVG attribute enumeration.

SVGElementEnum SVG element enumerations.

SVGGroupId Enumeration of SVG group id.

SVGHandler Contains SVG Data structure and API to create/load/edit SVG Documents DOM Observe Pattern Clarification. The methods here are pretty straightforward. It provides function to read/write or search XML data representing the WSN map specification.

XPathScanner Implementation of searching of element in svg document by XPath.

Package bsl.mapeditor.mapEngine.visualisation

VisMode Visualisation mode enumeration

VisualisationAPI Contains functions that creates the visualisation and handling effect on the map component. i.e. how room objects can be binded together or when objects are selected, certain parts are highlighed, etc.

Object Insertion : 1) Set mode; 2) Set currently inserting; 3) Set starting coordinate and related information for visualisation; 4) Once process is finished, alert SVG Handler to insert the object and reset all modes obj insertion has to be set first (currently inserting). Corrsponding visualisation of how the object is insert should than be displayed corrsponding to where the mouse is at i.e. for rooms, once the top left is set, the mouse should indicate where the bottom right corner of the room is (the size of the room changes according to the mouse position).

Package bsl.mapeditor.mapEngine.WSNMeta

WSNMeta API This class provide utilitites to add or modify custom element for storing more information (meta data) into SVG document.

WSNMeta attribute Enumeration of available attributes for meta data.

WSNMeta element Enumeration of available elements for meta data.

WSNMeta Property Enumeration of available property for meta data.

Javadoc example

Class MapEngineAPI

Contains and reference all data structures of the map ui components and associated high level methods. Contains: VisHandler and SvgHandler. Visualisation Handler controls the visualisation aspect, i.e. how SVG elements are displayed during insertion, selection etc. Once Visualisation Handler finishes the visualisation, the SVG element can than be inserted into the SVG document using the SVG handler. The SVG Handler controls the SVG related document API and the SVG data structure. This class is a singleton.

Declaration

public class MapEngineAPI
extends java.lang.Object

Field summary

- **isInsertingSVG**
- **Px_To_M_Ratio**

Method summary

- **alter_polygon_room_corner(SVGElement, int, float, float)** Alters the coordinate of the (index)th control point.
- **cancel_insertion()** Cancel the insertion process.
- **checkPolyRoomCorner(String, int, int)** Check the corner of the polygon room.
- **clearSelection()** Clear all selection objects.
- **deleteElement(SVGElement)** Delete the SVG element.
- **deleteMapobject(Mapobject)** Delete the map object.
- **documentLoaded()** Check if there is a document loaded.
- **finish_insertDoorObject()** Finish the insertion of door object.
- **finish_insertFurniture()** Finish the insertion of furniture.
- **finish_insertPIRObject()** Finish the insertion of PIR sensor object.
- **finish_insertPMObject()** Finish the insertion of pressure mat object.
- **finish_insertPolyRoom()** Finish the insertion of polygon room.
- **finish_insertRectangularRoom()** Finish the insertion of rectangular room.

finish_insertWayPoint() Finish the insertion of label name ('waypoint').

getDegreePIRCenter(Point2D.Float, Point2D.Float) Get the center degree of PIR sensor.

getDistance(int, int, int, int) Get the SVG coordinate distance between two SVG coordinate points.

getMapAPI() Returns a MapAPI singleton class.

getParentCanvas() Get the parent canvas.

getPx_To_M_Ratio() Get SVG pixel to meter ratio.

getRealWorldDistance_M(double) Get the real world distance.

getRealWorldDistance_M(float) Get the real world distance.

getRealWorldDistance_M(int, int, int, int) Get the real world distance.

getSVG_Handler() Get SVG handler.

getSVGDistanceFromRealWorld_M(float) Get the SVG coordinate distance from the map scale.

getVISUAL_Handler() Get the visualisation handler.

hide_CursorVis() Hide cursor visualisation.

hide_WallIntersectionVis() Hide wall intersection visualisation.

init_insertDoorObject() Initialise door object insertion.

init_insertFurniture() Initialise furniture insertion.

init_insertLine_VIS(int, int) Initiate visualisation for drawing lines.

init_insertPIR_VIS(int, int) Initialise PIR sensor visualisation.

init_insertPIRObject() Initialise PIR sensor object insertion.

init_insertPMObject() Initialise pressure mat object insertion.

init_insertPolyRoom() Initialise polygon room visualisation.

init_insertRect_VIS(int, int) Initiate visualisation of rectangular room.

init_insertRectangularRoom() Initialise rectangular room insertion.

init_insertWayPoint() Initialise label name ('waypoint') visualisation.

init_PolyRoom_vis(int, int) Initialise polygon room insertion.

insert_CursorVis(int, int) Insert cursor visualisation.

insert_WallIntersectionVis(int, int, int, int) Initialise wall intersection visualisation.

isIsInsertingSVG()

loadSVGFile(URI) Load an existing SVG file from file system.

move_CursorVis(int, int) Move cursor visualisation.

move_WallIntersectionVis(int, int, int, int) Move wall intersection visualisation.

moveSelection(int, int) Move selection visualisation.

newSVGFile() Create a new SVG File.

remove_CursorVis() Remove cursor visualisation.

remove_InsertionVIS() Remove current visualisation component.

remove_WallIntersectionVis() Remove wall intersection visualisation.

resize_insertLine_Vis(int, int) Resize line drawing visualisation.

resize_insertPIR_Vis(int, int, int, int) Resize PIR sensor visualisation.

resize_insertRectangle_Vis(int, int, int, int) Resize rectangular room insertion.

saveSVGFile(String) Save the current SVG data model into file.

setDocumentChangeComplete() This is used to notify observer classes that something has changed.

setInsertionMode() Set visualisation mode to insertion.

setIsInsertingSVG(boolean)

setLinearPathAttributes(SVGElement, String, ArrayList) Create SVG linear path attribute with supplied coordinates.

setLineAttributes(SVGElement, String, float, float, float, float) Set the line attributes.

setParentCanvas(MapCanvas) Set the parent canvas.

setPIRAttributes(SVGElement, String, float, float, float, float, float) Set the PIR sensor attributes.

setPx_To_M_Ratio(float) Set SVG coordinate to meter ratio.

setRectangleAttributes(SVGElement, String, float, float, float, float) Set the rectangle attributes.

setSelection(String) Set object to selected.

setSelectionMode() Set visualisation mode to Selection.

setSVG_Handler(SVGHandler) Set the SVG handler.

setTextAttributes(SVGElement, String, float, float, float, int, String) Set the text attributes.

setVISUAL_Handler(VisualisationAPI) Set the visualisation handler.

update_PolyRoom_vis(int, int, int, int) Update polygon room visualisation from old (x,y) coordinate to new (x,y) coordinate.

updatePolyRoomCoord() Update the polygon room coordinate points.

Fields

- public static float **Px_To_M_Ratio**
- public boolean **isInsertingSVG**

Methods

- **alter_polygon_room_corner**

  `public void` **alter_polygon_room_corner**`(SVGElement` **room**`,`
  `int` **index**`, float` **new_x**`, float` **new_y**`)`

  - **Description**

    Alters the coordinate of the (index)th control point.

  - **Parameters**

    * `room` – room object
    * `index` – index of the control point within this room object
    * `new_x` – new x coordinate
    * `new_y` – new y coordinate

- **cancel_insertion**

  `public void` **cancel_insertion**`()`

  - **Description**

    Cancel the insertion process.

- **checkPolyRoomCorner**

  `public boolean` **checkPolyRoomCorner**`(java.lang.String` **room_id**`, int`
  x`, int` **y**`)`

- **Description**

  Check the corner of the polygon room.

- **Parameters**

  * `room_id`
  * `x`
  * `y`

- **Returns** false

• **clearSelection**

`public void` **clearSelection**`()`

- **Description**

  Clear all selection objects. This will revert all object selection visualisation and back to its original representation.

• **deleteElement**

`public void` **deleteElement**`(SVGElement` **element**`)`

- **Description**

  Delete the SVG element.

- **Parameters**

  * `element`

• **deleteMapobject**

`public void` **deleteMapobject**`(svg.components.Mapobject` **o**`)`

- **Description**

  Delete the map object.

- **Parameters**

  * `o`

• **documentLoaded**

`public boolean` **documentLoaded**`()`

- **Description**

  Check if there is a document loaded.

- **Returns** Return true if the file exists.

- **finish_insertDoorObject**
  `public void` **finish_insertDoorObject**`()`
  - **Description**
    Finish the insertion of door object.

- **finish_insertFurniture**
  `public void` **finish_insertFurniture**`()`
  - **Description**
    Finish the insertion of furniture.

- **finish_insertPIRObject**
  `public void` **finish_insertPIRObject**`()`
  - **Description**
    Finish the insertion of PIR sensor object.

- **finish_insertPMObject**
  `public void` **finish_insertPMObject**`()`
  - **Description**
    Finish the insertion of pressure mat object.

- **finish_insertPolyRoom**
  `public void` **finish_insertPolyRoom**`()`
  - **Description**
    Finish the insertion of polygon room.

- **finish_insertRectangularRoom**
  `public void` **finish_insertRectangularRoom**`()`
  - **Description**
    Finish the insertion of rectangular room.

- **finish_insertWayPoint**
  `public void` **finish_insertWayPoint**`()`

- **Description**

  Finish the insertion of label name ('waypoint').

- **getDegreePIRCenter**

  `public static float` **getDegreePIRCenter**`(`
  `java.awt.geom.Point2D.Float` **location**`,`
  `java.awt.geom.Point2D.Float` **target**`)`

  - **Description**

    Get the center degree of PIR sensor.

  - **Parameters**

    * `location`
    * `target`

  - **Returns** Return float value of degree.

- **getDistance**

  `public static float` **getDistance**`(int` **svg_x1**`, int` **svg_y1**`,`
  `int` **svg_x2**`, int` **svg_y2**`)`

  - **Description**

    Get the SVG coordinate distance between two SVG coordinate points.

  - **Parameters**

    * `svg_x1`
    * `svg_y1`
    * `svg_x2`
    * `svg_y2`

  - **Returns** Return float distance between two SVG coordinate points.

- **getMapAPI**

  `public static MapEngineAPI` **getMapAPI**`()`

  - **Description**

    Returns a MapAPI singleton class.

  - **Returns** Return `map_api`.

- **getParentCanvas**

  `public MapCanvas` **getParentCanvas**`()`

  - **Description**

    Get the parent canvas.

  - **Returns** Return `parent_canvas`.

- **getPx_To_M_Ratio**

  `public static float` **getPx_To_M_Ratio**`()`

  - **Description**

    Get SVG pixel to meter ratio.

  - **Returns** Return the ratio pixel to m.

- **getRealWorldDistance_M**

  `public static float` **getRealWorldDistance_M**`(double` **distance_svg**`)`

  - **Description**

    Get the real world distance.

  - **Parameters**

    * `distance_svg`

  - **Returns** Return the value of distance (in m).

- **getRealWorldDistance_M**

  `public static float` **getRealWorldDistance_M**`(float` **distance_svg**`)`

  - **Description**

    Get the real world distance.

  - **Parameters**

    * `distance_svg`

  - **Returns** Return the value of distance (in m).

- **getRealWorldDistance_M**

  `public static float` **getRealWorldDistance_M**`(int` **svg_x1**`,`
  `int` **svg_y1**`, int` **svg_x2**`, int` **svg_y2**`)`

  - **Description** Get the real world distance.
  - **Parameters**
    * `svg_x1`
    * `svg_y1`
    * `svg_x2`
    * `svg_y2`
  - **Returns** Return the value of distance between two coordinates (in m).

- **getSVG_Handler**
  `public svg.SVGHandler` **getSVG_Handler**`()`
  - **Description**
    Get SVG handler.
  - **Returns** Return svgHandler.

- **getSVGDistanceFromRealWorld_M**
  `public static float` **getSVGDistanceFromRealWorld_M**`(`
  `float` **realWorldDistance**`)`
  - **Description**
    Get the SVG coordinate distance from the map scale.
  - **Parameters**
    * `realWorldDistance`
  - **Returns** Return the value of distance (in pixel).

- **getVISUAL_Handler**
  `public visualisation.VisualisationAPI` **getVISUAL_Handler**`()`
  - **Description**
    Get the visualisation handler.
  - **Returns** Return visualHandler.

- **hide_CursorVis**
  `public void` **hide_CursorVis**`()`

  - **Description**

    Hide cursor visualisation.

- **hide_WallIntersectionVis**

  `public void` **hide_WallIntersectionVis**`()`

  - **Description**

    Hide wall intersection visualisation.

- **init_insertDoorObject**

  `public void` **init_insertDoorObject**`()`

  - **Description**

    Initialise door object insertion.

- **init_insertFurniture**

  `public void` **init_insertFurniture**`()`

  - **Description**

    Initialise furniture insertion.

- **init_insertLine_VIS**

  `public void` **init_insertLine_VIS**`(int` **pos_x**`, int` **pos_y**`)`

  - **Description**

    Initiate visualisation for drawing lines.

  - **Parameters**

    * `pos_x`
    * `pos_y`

- **init_insertPIR_VIS**

  `public void` **init_insertPIR_VIS**`(int` **pos_x**`,`
  `int` **pos_y**`)`

  - **Description**

    Initialise PIR sensor visualisation.

  - **Parameters**

    * pos_x
    * pos_y

- **init_insertPIRObject**
  `public void` **init_insertPIRObject**`()`
  - **Description**
    Initialise PIR sensor object insertion.
- **init_insertPMObject**
  `public void` **init_insertPMObject**`()`
  - **Description**
    Initialise pressure mat object insertion.
- **init_insertPolyRoom**
  `public void` **init_insertPolyRoom**`()`
  - **Description**
    Initialise polygon room visualisation.
- **init_insertRect_VIS**
  `public void` **init_insertRect_VIS**`(int` **pos_x**`, int` **pos_y**`)`
  - **Description**
    Initiate visualisation of rectangular room.
  - **Parameters**
    * pos_x
    * pos_y
- **init_insertRectangularRoom**
  `public void` **init_insertRectangularRoom**`()`
  - **Description**
    Initialise rectangular room insertion.
- **init_insertWayPoint**
  `public void` **init_insertWayPoint**`()`

  - **Description**

    Initialise label name ('waypoint') visualisation.

- **init_PolyRoom_vis**

  `public void` **init_PolyRoom_vis**`(int` **pos_x**`, int` **pos_y**`)`

  - **Description**

    Initialise polygon room insertion.

  - **Parameters**

    * `pos_x` – start x
    * `pos_y` – start y

- **insert_CursorVis**

  `public void` **insert_CursorVis**`(int` **pos_x**`, int` **pos_y**`)`

  - **Description**

    Insert cursor visualisation. Currently, a cursor is only a red circle signifying a position on the map.

  - **Parameters**

    * `pos_x`
    * `pos_y`

- **insert_WallIntersectionVis**

  `public void` **insert_WallIntersectionVis**`(int` **x1**`, int` **y1**`, int` **x2**`, int` **y2**`)`

  - **Description**

    Initialise wall intersection visualisation.

  - **Parameters**

    * `x1`
    * `y1`
    * `x2`
    * `y2`

- **isIsInsertingSVG**

  `public boolean` **isIsInsertingSVG**`()`

- **loadSVGFile**
  `public void` **loadSVGFile**`(java.net.URI` **path**`)`
  - **Description**
    Load an existing SVG file from file system.
  - **Parameters**
    * `path`
- **move_CursorVis**
  `public void` **move_CursorVis**`(int` **pos_x**`, int` **pos_y**`)`
  - **Description**
    Move cursor visualisation.
  - **Parameters**
    * `pos_x`
    * `pos_y`
- **move_WallIntersectionVis**
  `public void` **move_WallIntersectionVis**`(int` **x1**`, int` **y1**`, int` **x2**`, int` **y2**`)`
  - **Description**
    Move wall intersection visualisation.
  - **Parameters**
    * `x1`
    * `y1`
    * `x2`
    * `y2`
- **moveSelection**
  `public void` **moveSelection**`(int` **displace_x**`, int` **displace_y**`)`
  - **Description**
    Move selection visualisation. When a object is selected and dragged, this function is called to visualisation the object's new position.

- **Parameters**
  - `displace_x`
  - `displace_y`

- **newSVGFile**
  `public void` **newSVGFile**`()`
  - **Description**
    Create a new SVG File.

- **remove_CursorVis**
  `public void` **remove_CursorVis**`()`
  - **Description**
    Remove cursor visualisation.

- **remove_InsertionVIS**
  `public void` **remove_InsertionVIS**`()`
  - **Description**
    Remove current visualisation component.

- **remove_WallIntersectionVis**
  `public void` **remove_WallIntersectionVis**`()`
  - **Description**
    Remove wall intersection visualisation.

- **resize_insertLine_Vis**
  `public void` **resize_insertLine_Vis**`(int x, int y)`
  - **Description**
    Resize line drawing visualisation.
  - **Parameters**
    - `x`
    - `y`

- **resize_insertPIR_Vis**
  `public void` **resize_insertPIR_Vis**`(int` **org_x**`, int` **org_y**`, int` **x**`, int` **y**`)`
  - **Description**
    Resize PIR sensor visualisation.
  - **Parameters**
    * `org_x`
    * `org_y`
    * `x`
    * `y`
- **resize_insertRectangle_Vis**
  `public void` **resize_insertRectangle_Vis**`(int` **org_x**`, int` **org_y**`, int` **width**`, int` **height**`)`
  - **Description**
    Resize rectangular room insertion.
  - **Parameters**
    * `org_x`
    * `org_y`
    * `width`
    * `height`
- **saveSVGFile**
  `public void` **saveSVGFile**`(java.lang.String` **path**`)`
  - **Description**
    Save the current SVG data model into file.
  - **Parameters**
    * `path`
- **setDocumentChangeComplete**
  `public void` **setDocumentChangeComplete**`()`

  - **Description**

    This is used to notify observer classes that something has changed.

- **setInsertionMode**

  `public void` **setInsertionMode**`()`

  - **Description**

    Set visualisation mode to insertion.

- **setIsInsertingSVG**

  `public void` **setIsInsertingSVG**`(boolean` **isInsertingSVG**`)`

- **setLinearPathAttributes**

  `public void` **setLinearPathAttributes**`(SVGElement` **element**`,`
  `java.lang.String` **id**`, java.util.ArrayList` **coord**`)`

  - **Description**

    Create SVG linear path attribute with supplied coordinates.

  - **Parameters**

    * `element`
    * `id`
    * `coord`

- **setLineAttributes**

  `public void` **setLineAttributes**`(SVGElement` **element**`,`
  `java.lang.String` **id**`, float` **x1**`, float` **y1**`, float` **x2**`, float` **y2**`)`

  - **Description**

    Set the line attributes.

  - **Parameters**

    * `element`
    * `id`
    * `x1`
    * `y1`
    * `x2`

  * y2

- **setParentCanvas**
  `public void` **setParentCanvas**`(MapCanvas` **parentCanvas**`)`

  - **Description**
    Set the parent canvas.
  - **Parameters**
    * parentCanvas

- **setPIRAttributes**
  `public void` **setPIRAttributes**`(SVGElement` **element**`, java.lang.String` **id**`, float` **src_x**`, float` **src_y**`, float` **distance**`, float` **centerDegree**`, float` **fov**`)`

  - **Description**
    Set the PIR sensor attributes.
  - **Parameters**
    * element
    * id
    * src_x
    * src_y
    * distance
    * centerDegree
    * fov

- **setPx_To_M_Ratio**
  `public static void` **setPx_To_M_Ratio**`(float` **Px_To_M_Ratio**`)`

  - **Description**
    Set SVG coordinate to meter ratio.
  - **Parameters**
    * Px_To_M_Ratio

- **setRectangleAttributes**
  `public void` **setRectangleAttributes**`(SVGElement` **element**`,`
  `java.lang.String` **id**`, float` **x1**`, float` **y1**`, float` **width**`,`
  `float` **height**`)`

  - **Description**

    Set the rectangle attributes.

  - **Parameters**

    * `element`
    * `id`
    * `x1`
    * `y1`
    * `width`
    * `height`

- **setSelection**
  `public void` **setSelection**`(java.lang.String` **id**`)`

  - **Description**

    Set object to selected. This will update the visualisation of this object.

  - **Parameters**

    * `id`

- **setSelectionMode**
  `public void` **setSelectionMode**`()`

  - **Description**

    Set visualisation mode to Selection.

- **setSVG_Handler**
  `public void` **setSVG_Handler**`(svg.SVGHandler` **SVG_Handler**`)`

  - **Description**

    Set the SVG handler.

  - **Parameters**

    * `SVG_Handler` –

- **setTextAttributes**
  `public void` **setTextAttributes**`(SVGElement` **element**`,`
  `java.lang.String` **id**`, float` **x1**`, float` **y1**`, float` **orientation**`,`
  `int` **fontsize1**`, java.lang.String` **content**`)`
  - **Description**
    Set the text attributes.
  - **Parameters**
    * `element`
    * `id`
    * `x1`
    * `y1`
    * `orientation`
    * `fontsize1`
    * `content`
- **setVISUAL_Handler**
  `public void` **setVISUAL_Handler**
  `(visualisation.VisualisationAPI` **VISUAL_Handler**`)`
  - **Description**
    Set the visualisation handler.
  - **Parameters**
    * `VISUAL_Handler`
- **update_PolyRoom_vis**
  `public void` **update_PolyRoom_vis**`(int` **old_x**`, int` **old_y**`,`
  `int` **new_x**`, int` **new_y**`)`
  - **Description**
    Update polygon room visualisation from old (x,y) coordinate to new (x,y) coordinate.
  - **Parameters**

    * old_x
    * old_y
    * new_x
    * new_y

- **updatePolyRoomCoord**
  `public void` **updatePolyRoomCoord**`()`
  - **Description**
    Update the polygon room coordinate points.

Appendix B. WSN Simulator

As mentioned earlier in Section 3.4, the WSN simulator is a software tool that is designed to simulate the subject's movement through the residential environment, and PIR and PM sensors respond in a binary manner to the subject's movement. WSN simulator has a module called "com.arni.wsnsimulator.api". This module contains 13 main packages and a total of 78 classes. Each class is briefly described but only one class is documented in detail, as a representative example. The reason why the author only gives the summary of the class in this appendix is because there are too many lines of code and the appendix would be too long, and the additional inclusion of these classes would not contribute significantly to the document.

Package com.arni.wsnsimulator.api.database api

Class database api The Database API needs to: 1) Initialise the database i.e. If it is the first time, setup tables, database properties and where to save the files; 2) Provides API to read/write data in and out of the database; 3) Provide API to transfer data from one source to the other; and 4) Shutdown the database.

Package com.arni.wsnsimulator.api.input

SVGMapHandler Contains SVG data structure and API to create/load/edit SVG documents. The methods here are pretty straightforward. It provides function to read/write or search XML data representing the WSN map specification.

XMLConfigFileReader Reads an XML Simulation configuration file and loaded into the simulation data structure. An XML config file can consists of schedule, people list and map information. It is recommended that all information are present, a schedule can exist without the people list however, the simulator will create default profile for people in the schedule list.

Package com.arni.wsnsimulator.api.Kernel

analysis api This class contains function that analysis the data created by the simulation, including: 1) Participants speed as a function of time; 2) Participants distance travel as a function of time; 3) Sensor info; and 4) Sensor coverage.

Kernel Kernel will host the scheduler and basic function dealing with simulation and running of the program.

runPathFindingAlgorithm Insert journey info, this thread will return the Path results only.

SimulateAlgorithm The simulation algorithm is contained here: 1) Get participant, get journey information and walking speed; 2) Retrieve map information; 3) Run path finding algorithm to get path; 4) Work out the timing from path and what sensors are triggered during the path. 4a) Work out the subjects location/grid at each time-step. 4b) What sensors are triggered during that time-step. Sensor info infrared and pressure mats $\rightarrow 0/1$; and 5) Send off data back in Simulator.java (responsible for read/write functions).

SimulateThread Implementation of Runnable interface to run simulation into separate thread.

SimulationProgressDialog Dialog window to display progress of simulation.

Simulator The simulator controls how the simulator is executed (extract data and configure from data structure, execute the simulation, and store the results). 1) Signal simulator is running (i.e. locked); 2) Load map and environment data (i.e. what sensor etc variable can be overridden from the map); 3) Load scheduler data; 4) Load path finding configure etc (SimulatorAlgorithm.java);

5) Run path finding algorithm and get path data (SimulatorAlgorithm.java); 6) Use the path to work out the sensor results and other information (SimulatorAlgorithm.java); 7) Write data into data structure; and 8) Signal simulation is complete (i.e. unlocked).

Simulator.simulator status Simulator status enumeration type: running and idle.

TimeDelay Enumeration of time delay.

Package com.arni.wsnsimulator.api.Kernel. TimeData

AbstractTimeData Abstract class for storing data for particular period of time.

DefaultTimeSeries Base class for storing list of AbstractTimeData.

SensorTimeData Implementation of AbstractTimeData for sensor.

SensorTimeSeries Extended class of DefaultTimeSeries.

Package com.arni.wsnsimulator.api.lookup

CustomGlobalLookup Custom implementation of AbsctractLookup Netbean feature.

LookupCollection Utility for lookup operation.

Package com.arni.wsnsimulator.api.map

DoorShapes Class for door object representation.

Furniture Class for furniture object representation.

Grid The grid is a representation of the SVG map that can be used for pathfinding and other analytical purposes. The grid is required to: 1) Create and maintain an accessible and searchable data structure; 2) Locate sensor tiles and register it; 3) Locate furniture and location destination tiles (furniture tiles should have cost added to the tile i.e. so that waypoint will try to go around it unless its a destination. Destination should be a shape, the tile used should be the center. Some maps uses text nodes as destinations, we need to support this as well; and 4) Register wall and obstacles. Grid is coordinate independent of screen resolution. The top left hand corner (i.e. tile 0) starts at (xLeftCoordinate, yUpperCoordinate). All query from SVG is mapped to this coordinate.

Grid.Tile A tile can contain a number of information, including: 1) Multiple sensor coverage; 2) If a physical object is on it. This may include: furniture, wall, door and opening.

GridObserver Implementation of observable grid.

LocationCache Implementation of location caching data.

MapCanvas Custom implementation of JSVGCanvas for displaying SVG documents.

Node This class provides methods for a node object.

Obstacle This class provides methods for an obstacle.

Path This class provides methods for a path.

PathFinding A* implementation for path finding.

SensorCoverage This class provides methods for defining the coverage area of the sensors.

SimObject An abstract object class representing an object in the simulator, i.e. can be a furniture (couch, bed, tv etc etc) or a wall and other obstacles.

SortedList This class provides methods for sorting an array of objects.

SvgMap This class is used to add obstacles and trajectories for people's movement.

TileSensorProperty This class is used by a tile to describe the sensor location and the meta-data information with regard to the sensor and this particular tile i.e. the probability of this sensor being triggered at this tile.

WayPointCache This class is used to create a cache for waypoint.

WayPointList Class for waypoint object representation.

Package com.arni.wsnsimulator.api.output

Excel Writer The class can generate spreadsheet files writing a whole rows at once, or individual row cells one at a time.

FileUtil A utility class to simplify different aspects of handling file and directory names.

HDF5 Exporter Converts data into HDF5 file format. Write WSN setup information, sensor table information and simulation data.

XMLConfigFileWriter Saves the XML config profile into a simulation config file format.

Package com.arni.wsnsimulator.api.people

People Class for People object representation.

PeopleAnimator Animate people representation.

PeopleNode This class is used to define a node for people.

PeopleNodeList This class is used to create a list of people's node.

Package com.arni.wsnsimulator.api.Scheduler

Event Class for event representation.

EventPhase Event phase enumerations.

Scenario This class is used to create scenario files which manually initiated.

ScheduleError Stated the error in scheduler.

Scheduler A scheduler contains a data structure hold a list of scenario with regards to a person and the event that will occur. This scheduler contains API on inserting, editing and extracting information on the time frame.

SchedulerList This class is used to view a list of schedulers.

SchedulerLocationValidityChecker This class tests the schedule continuity. i.e. for every person, the locations must be continues across all the events. If not, the function will return a false.

ScriptedAction Scripted action enumerations.

ScriptedEvent A scripted event is attached to a persons transit event. There are triggers to start/end an action. Start, during or end of the persons transit event. A scripted event is only meant to effect the action of one object i.e. sensor.

Task This class listed the category of task.

TaskType This class listed different types of task.

TimingType This class listed two different time options: task duration and mobility duration.

TransitEvent This class is used to define transit event.

Package com.arni.wsnsimulator.api.output

PIRSensor This class provides methods for a PIR sensor object.

PressureMat This class represent pressure mat sensor object.

Sensor Abstract class of sensor.

SensorList This class is for storing list of sensors.

SensorType Enumeration of sensor type.

Package com.arni.wsnsimulator.api.SensorAdjacency

SensorAdjacency Work out the adjacency connectivity matrix.

SensorConnectivity Generate a sensor connectivity string format using the grid data structure.

Package com.arni.wsnsimulator.api.svg

AnimationAction Abstract class for animation.

AnimationCurrentQueue This current contains the current animated object in a sorted order from the one that finishes earliest to the last.

AnimationObject This class is used to represent the animation objects.

AniPath This class is used to represent the animation path.

MovementAction This class is for animating movement.

SensorSortableResult This class is used to sort the results list based on time values.

SetSensorVisibleAction This class is for showing or hiding sensor coverage area

StationaryAction This class is used to define stationary action.

SVGParser This class is used to parse the SVG objects.

visualisation api The visualisation API is responsible for providing visualisation of the simulator, these includes: 1) Animation of people location according to time; 2) Layout of path; 3) Labeling of events along path; 4) Visualisation of triggered sensors according to the time that it is triggered; and 5) Responsible for when to display or not to display these items according to the visualisation configuration. Currently, the visualisation is only set to display the last simulation result.

VisualisationThread To thread is to control the animation of SVG objects. Using the default SVG animation elements are problematic. This allows us to control when it start or stop. This thread is primarily responsible for drawing the persons traverse and sensor triggering.

VisualiseObject This class is used to list visualise objects.

Package com.arni.wsnsimulator.api.xml

sml attributes SML attributes enumeration.

SensorConnectivity Simulator element definitions enumeration.

Javadoc example

Class SVGMapHandler

Contains SVG data structure and API to create/load/edit SVG documents. The methods here are pretty straightforward. It provides function to read/write or search XML data representing the WSN map specification.

Declaration

public class SVGMapHandler
extends java.util.Observable

Method summary

ClearMapCache(boolean) Clear the current map information.
dispose() Dispose object.
getCanvas() Get MapCanvas object.
getDocument() Get SVGDocument.
getDoorSvgList() Get a list of doors string.
getFilePath() Get file path.
getFurnitureID() Get a list of furniture id.
getFurnitureList() Get and set the furniture name and furniture object.
getFurnitureMap() Get and set the furniture name and furniture object.
getGroup(SVGDocument, String) Get a group of element by group id.
getMapLoader() Singleton pattern implementation to get SVGMapHandler object.
getPropertyValue(Element, String) Get the value of property name.
getRoomSvgList() Get a list of rooms name.
getSensorList() Get a list of sensors name.
getZ1(Element) Get the height of furniture.
getZ2(Element) Get the height from the ground.
loadSVGFile(String, boolean) Load SVG file.
parseFurnitureGroup(SVGDocument) Parse the group of furniture object.
parseSensorGroup(SVGDocument) Parse the group of sensors.
parseWallDoorGroup(SVGDocument) Parse the group of wall objects.
parseWaypoint(SVGDocument) Parse the group of waypoint.
setMapCanvas(MapCanvas) Set MapCanvas object.

Methods

- **ClearMapCache**

  `public void` **ClearMapCache**`(boolean` **broadcast**`)`

– **Description**

Clear the current map information.

- **dispose**

  `public void` **dispose**`()`

  – **Description**

  Dispose object.

- **getCanvas**

  `public com.arni.wsnsimulator.api.map.MapCanvas` **getCanvas**`()`

  – **Description**

  Get MapCanvas object.

  – **Returns** Return mapCanvas.

- **getDocument**

  `public SVGDocument` **getDocument**`()`

  – **Description**

  Get SVGDocument.

  – **Returns** Return document.

- **getDoorSvgList**

  `public java.util.ArrayList` **getDoorSvgList**`()`

  – **Description**

  Get a list of doors string.

  – **Returns** Return doorSvgList.

- **getFilePath**

  `public java.lang.String` **getFilePath**`()`

  – **Description**

  Get file path.

- **Returns** Return filepath.

- **getFurnitureID**

  `public java.lang.String[]` **getFurnitureID**`()`

  - **Description**

    Get a list of furniture id.

  - **Returns** Return the list of furniture id.

- **getFurnitureList**

  `public java.util.HashMap` **getFurnitureList**`()`

  - **Description**

    Get and set the furniture name and furniture object.

  - **Returns** Return furnitureList.

- **getFurnitureMap**

  `public java.util.HashMap` **getFurnitureMap**`()`

  - **Description**

    Get and set the furniture name and furniture object.

  - **Returns** Return furnitureList.

- **getGroup**

  `public org.w3c.dom.Element` **getGroup**`(SVGDocument` **doc**`,`
  `java.lang.String` **groupId**`)`

  - **Description**

    Get a group of element by group id.

  - **Parameters**

    * `doc`
    * `groupId`

  - **Returns** Return null if nothing is found.

- **getMapLoader**

  `public static SVGMapHandler` **getMapLoader**`()`

- **Description**

  Singleton pattern implementation to get SVGMapHandler object.

- **Returns** Return loadMap.

- **getPropertyValue**

  `public static java.lang.String` **getPropertyValue**`(`
  `org.w3c.dom.Element` **element**`, java.lang.String` **propertyName**`)`

  - **Description**

    Get the value of property name.

  - **Parameters**

    * `element`
    * `propertyName`

  - **Returns** Return the value of property.

- **getRoomSvgList**

  `public java.util.ArrayList` **getRoomSvgList**`()`

  - **Description**

    Get a list of rooms name.

  - **Returns** Return roomSvgList.

- **getSensorList**

  `public java.util.ArrayList` **getSensorList**`()`

  - **Description**

    Get a list of sensors name.

  - **Returns** Return sensorInSVGList.

- **getZ1**

  `public static float` **getZ1**`(org.w3c.dom.Element` **element**`)`

  - **Description**

    Get the height of furniture.

  - **Returns** Return the float value of z1.

- **getZ2**

  `public static float` **getZ2**`(org.w3c.dom.Element` **element**`)`

  - **Description**

    Get the height from the ground.

  - **Returns** Return the float value of z2.

- **loadSVGFile**

  `public void` **loadSVGFile**`(java.lang.String` **file_path**`,`
  `boolean` **broadcast**`)`

  - **Description**

    Load svg file.

  - **Parameters**

    * `file_path`
    * `broadcast`

- **parseFurnitureGroup**

  `public void` **parseFurnitureGroup**`(SVGDocument` **doc**`)`

  - **Description**

    Parse the group of furniture object.

  - **Parameters**

    * `doc`

- **parseSensorGroup**

  `public void` **parseSensorGroup**`(SVGDocument` **doc**`)`

  - **Description**

    Parse the group of sensors.

  - **Parameters**

    * `doc`

- **parseWallDoorGroup**

  `public void` **parseWallDoorGroup**`(SVGDocument` **doc**`)`

- **Description**

  Parse the group of wall objects.

- **Parameters**

  * doc

- **parseWaypoint**

  `public void` **parseWaypoint**`(SVGDocument` **doc**`)`

  - **Description**

    Parse the group of waypoint.

  - **Parameters**

    * doc

- **setMapCanvas**

  `public void` **setMapCanvas**`(com.arni.wsnsimulator.api.map.MapCanvas` **mapcanvas**`)`

  - **Description**

    Set MapCanvas object.

  - **Parameters**

    * mapcanvas

Members inherited from class Observable

`java.util.Observable`

- `public synchronized void` **addObserver**`(Observer` **arg0**`)`
- `protected synchronized void` **clearChanged**`()`
- `public synchronized int` **countObservers**`()`
- `public synchronized void` **deleteObserver**`(Observer` **arg0**`)`
- `public synchronized void` **deleteObservers**`()`
- `public synchronized boolean` **hasChanged**`()`
- `public void` **notifyObservers**`()`
- `public void` **notifyObservers**`(java.lang.Object` **arg0**`)`
- `protected synchronized void` **setChanged**`()`

Appendix C. List of MATLAB Code

In this appendix, the author presents the MATLAB code that is used in this thesis.

- The code called “residentprofile.m” is used to generate a list of residents. Each list may consist of one, two or three persons with different ages, heights, genders and walking speeds. Age was selected randomly from a uniform distribution over the interval [45,87] years. Random BMI and height parameters are also randomly generated using a normal distribution with means and standard deviations drawn from published population statistics [200]. The average simulated walking speed, calculated from these ages and BMIs. The resulting output is used as input data to a code called “outputXML.m”. The “outputXML.m” is a code that is used to modify the XML file, by adding a new list of residents. A detailed explanation of the resident profile can be found in Sections 4.2.1 and 5.3.1.

- The code called “oldalgorithm.m” is used to analyse sensor data and to differentiate fall events from normal activities, based on inactivity duration. A detailed explanation of the methodology employed in this code can be found in Section 4.2.2.

- The code called “newalgorithm.m” is used to track the movement of multiple persons and to unobtrusively detect falls when they occur. A detailed explanation for the methodology used in this code can be found in Section 5.3.2.

Similar to the previous appendix, the author only lists the major functions for each package due to a large number of lines of code.

Resident Profile

```
function [age,gender,height,walkspeed,bmi]=residentprofile(numberOfPersons, data,↩
    numberOfoption)
% age for both sexes
men_age=cell2mat(data(1));
women_age=cell2mat(data(2));
% body mass index (bmi) for both sexes
men_bmi=cell2mat(data(3));
women_bmi=cell2mat(data(4));
% height for both sexes
men_height=cell2mat(data(5));
women_height=cell2mat(data(6));
% walkspeed for both sexes
men_walkspeed=cell2mat(data(7));
women_walkspeed=cell2mat(data(8));
% number of persons
if numberOfoption == 1 %one person
:
elseif numberOfoption == 2 %two person
:
elseif numberOfoption == 3 %three person
:
end
end
```

```
function outputXML(age,gender,height,walkspeed)
xmls=dir('*.xml');
[numxml dum] = size(xmls); %number of XML files
[numpersons dum] = size(age); %number of persons

l=0;
j=1;
if numxml > 0
    while(j<=numpersons)
        for k=1:1:numdir
            l=l+1;
            filename = xmls(k).name;
            xdoc = xmlread(filename);
            :
            :
```

```
            end
            xmlwrite(strcat('.\out\test',num2str(1),'.xml'),xdoc); %write XML ↩
    document
        end
    end
end
end
```

Unobtrusive Falls Detection for a Single Person

```
function oldalgorithm
clc, close all;clear all
DirSource='filename';
generateData(DirSource)
end
```

```
function generateData(DirSource)
sDirSource=dir(strcat(DirSource,'\','*.xls'));
[NumofDir dumm]=size(sDirSource);

for k=1:1:NumofDir
Excel_Files=strcat(DirSource,'\',sDirSource(k).name);
[ndata,txt,alldata] = xlsread(Excel_Files, 'Profile2');

%start analysis process
[DataofPir DataofPressure DataofFallsAlert Decision]=fallsdetection(ndata);

% save data of ambient sensors(PIR and PM sensors), triggered alert record and ↩
    analysis results
[pathstr, name, ext, versn] = fileparts(Excel_Files);
DirectoryName=(Excel_Files(1:end-4));
mkdir(DirectoryName);

PIR_File=strcat(DirectoryName,'\', name,'_PIR','.mat');
Pressure_File=strcat(DirectoryName,'\',name,'_Pressure','.mat');
FallsAlert_File=strcat(DirectoryName,'\', name,'_FallsAlert','.mat');
Decision_File=strcat(DirectoryName,'\', name,'_Decision','.mat');

save(PIR_File, 'DataofPir');
save(Pressure_File, 'DataofPressure');
save(FallsAlert_File, 'DataofFallsAlert');
save(Result_File, 'Decision');
end
end
```

Unobtrusive Falls Detection with Multiple Persons

```
function newalgorithm
clc, close all;clear all
DirSource='filename';
generateData(DirSource)
end
```

```
function generateData(DirSource)
sDirSource=dir(strcat(DirSource,'\','*.xls'));
[NumofDir dumm]=size(sDirSource);

adjacencygraph = xlsread('.\adjacencygraph.xls');
reachabilitymatrix = xlsread('.\reachabilitymatrix.xls');

for k=1:1:NumofDir
    Excel_Files=strcat(DirSource,'\',sDirSource(k).name);
    dataSensors = xlsread(Excel_Files, 'Profile1');

%start analysis process
[DataofUpperPIR, DataofLowerPIR, DataofPressure, DataofFallsAlert, Decision]= ↩
    test(dataSensors,adjacencygraph,reachabilitymatrix);

% save data of ambient sensors(upper PIR, lower PIR and PM sensors), triggered ↩
    alert record and analysis results
[pathstr, name, ext, versn] = fileparts(Excel_Files);
DirectoryName=(Excel_Files(1:end-4));
mkdir(DirectoryName)

UpperPIR_File=strcat(DirectoryName,'\', name,'_UpperPIR','.mat');
LowerPIR_File=strcat(DirectoryName,'\', name,'_LowerPIR','.mat');
Pressure_File=strcat(DirectoryName,'\', name,'_Pressure','.mat');
FallsAlert_File=strcat(DirectoryName,'\', name,'_FallsAlert','.mat');
Decision_File=strcat(DirectoryName,'\', name,'_Decision','.mat');

save(UpperPIR_File, 'DataofUpperPIR');
save(LowerPIR_File, 'DataofLowerPIR');
save(Pressure_File, 'DataofPressure');
save(FallsAlert_File, 'DataofFallsAlert');
save(Decision_File, 'Decision');
end
end
```

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