How to Build Better Fall Detection Technology: A Search for Characteristics Unique to Falls and Methods to Robustly Evaluate Performance

Robert William Broadley

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List of Abbreviations

ADL Activities of Daily Living

AUC Area Under Curve

BBS Berg Balance Scale

BMI Body Mass Index

CCTV Closed-Circuit Television

FN False Negatives

FP False Positives

FPRT False Positive Rate over Time

FSHC Four Seasons Health Care

IQR Interquartile Range

LOB Loss of Balance

LTC Long-Term Care

MCC Mathews Correlation Coefficient

N Negative cases (in binary classification)

NHS National Health Service (UK)

NICE National Institute of Health Care Excellence (UK)

NPV Negative Predictive Value

P Positive cases (in binary classification)

PERS Personal Emergency Response System

PR Precision-Recall

ROC Receiver Operating Characteristic

RSS Root Sum of Squares

SD Standard Deviation

STRATIFY St. Thomas's Risk Assessment Tool in Falling Elderly Inpatients

SVM Support Vector Machine

TP True Positives

TUG Timed Up and Go

UK United Kingdom

USA United States of America

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Statement of Contribution

During my PhD candidature, I have played a major role in all the studies contained in this thesis. I carried out the review of previous approaches to fall detection (Chapter 3), identified the limitations of how the research was conducted and formulated the proposed framework for future development. I devised the study on methods for the real-world evaluation of fall detection technology (Chapter 4) and carried out all stages of the systematic search, review of articles, formulated the proposed method and wrote the draft manuscript.

The pilot study (Chapter 5) was funded by the Greater Manchester Allied Health Science Network. I devised the protocol for this study, developed the software which displayed the instructions to participants and conducted all data analysis, including the development and testing of the posture classification algorithms.

The collection of the real-world dataset (Chapter 6) was funded by the Dowager Countess Eleanor Peel Trust and carried out by a small team from the University of Salford in collaboration with Four Seasons Health Care. I played a major role in the design and delivery of this project. I had extensive input on the design of the protocol, developed the pathways for participant recruitment and supported the participating care homes. My role additionally included the provision of training to care homes on participant recruitment and data collection. I managed the entirety of the data collection during the second half of the project (July 2017 to June 2018). I devised and developed all the software described in this thesis which was used during the management, processing and analysis of the data. All analysis presented in this thesis was devised and carried out by myself, except for the identification of the fall signals, where Malcolm Granat was the second-rater.

Abstract

Falls can have severe consequences for older adults, such as bone fractures and long periods unable to get up from the ground, known as a long-lie. The capability to automatically detect falls would reduce long-lies through ensuring prompt arrival of assistance and would be valuable in fall risk assessment and fall prevention research. This research aimed to identify why existing wearable fall detection technology has not achieved acceptable performance and where further development should focus.

There have been a plethora of attempts at fall detection; real-world testing is in an embryonic stage, nevertheless, it is clear performance has been poor. The focus has been on the testing of complete system performance, most commonly with acted falls, and it has been unclear how to improve performance. A new framework for the development of fall detection is proposed which promotes targeted investigation of how real-world performance can be improved. An improved method to quantify real-world performance is also proposed based on a systematic review of previous approaches. To prepare for the analysis of a real-world dataset, a pilot study was conducted which focused on the development and testing of posture classification algorithms.

One of the world's largest datasets of real-world falls and activities of daily living was collected over 2 years in collaboration with 17 care homes across Scotland and the north of England. Twenty fall signals were extracted from 1,919 days of thigh-worn accelerometer recordings collected with 42 participants. Analysis of the data focused on falls from an upright to a sedentary (sitting or lying) posture, 16 falls met this criterion and were included in the analysis. To allow the data to be thoroughly checked for quality, the dataset was reduced to 104 days, from which 4,293 upright to sedentary transitions were extracted (including the 16 falls).

This study was the first to: discern that falls may be too diverse to classify as a single group and focus on a subtype of fall, use posture transitions to select events for analysis, assess the importance of peak jerk and vertical velocity for fall detection, and investigate the occurrence of multiple impacts during falls. The results demonstrated that the core features used previously do not yield sufficient separation of the falls to allow detection without high rates of false positives. For the first time, it was shown that (1) a rapid increase in deceleration may be more indicative of a fall than the peak deceleration, and (2) multiple impacts occur frequently in falls but not other movements.

Chapter 1

Introduction

Falls in older adults present a major healthcare challenge that is set to grow in the coming years due to population ageing [1]. Falls have severe consequences for the individual, their family, and society as a whole, as they often lead to a decline in the individual's health. Those who fall often struggle to get up unaided, therefore where assistance is not close by, falls can result in a long-lie [2,3]. A long-lie is an unintentional, extended period spent on the ground and has been associated with a decline in health from which individuals often do not recover [4–6]. Reliable detection of falls as part of an alarm system is crucial to minimise the consequences of falls and long-lies. In addition to applications in alarm systems, the ability to accurately detect falls and log their occurrence has the potential to revolutionise fall risk assessment and fall prevention research.

There has been a great deal of research into fall detection technology with over 200 published articles since 1998 [7–12]. The vast majority of tests of fall detection technology have used data from falls acted out in a laboratory by healthy, young adults [7–10,13,14]. The use of so-called "simulated falls" allows a relatively large number of falls to be collected in a short period, which has made it an attractive approach, particularly in the early stages of development. However, research has shown that there are differences between these simulated falls and real falls and that the results of tests on simulated falls do not transfer to the real-world [15–18]. Approaches which detected over ninety percent of simulated falls detected less than half the falls in a set of real-world data [17–19]. In addition, when tested on real-world data the rate of false positives has been much higher than expected based on the performance reported from tests on simulated falls [17–20].

The use of real-world data for fall detection research has been limited due to challenges in recording real falls [17]. Where real-world data has been used, the focus has been on testing prototype fall detection systems and algorithms. Consequently, little has been learned about how real falls can be detected robustly, no tangible improvements in real-world performance have been made and performance remains poor. Using one of the largest studies of fall detection technology as an example, Lipsitz et al. [21] tested a pendant-based fall alarm produced by Royal Philips (Amsterdam, Netherlands) and found that only nineteen percent of falls were detected and that only thirteen percent of the alarms raised corresponded to an actual fall. It was evident that a new approach was needed if significant improvements in performance were to be found and the use of real-world data to test systems, while important, was not sufficient.

The central aim of the research which underpins this thesis was to identify why existing wearable fall detection technology has not achieved acceptable performance and where further development should focus. There were five sub-aims: (1) to formulate a new framework for the development of fall detection technology, (2) to identify how fall detection performance should be quantified, (3) to test the activPAL3 device as an instrument to record fall signals, (4) to collect a real-world dataset of falls and activities of daily living comparable in size to the largest used in previous studies, and (5) to analyse real-world fall data in line with the proposed framework such that the main aim is achieved.

To understand why existing approaches have not achieved acceptable performance it was important to evaluate how fall detection research has been conducted; after all, if the methods used to develop the technology are not appropriate then one cannot expect to make progress. There are two key stages of development, the first is the design, the second is how the performance is evaluated; this is a cyclic process so the evaluation needs to inform future design. Sub-aim one addresses the process of identifying how to improve the design of fall detection technology following an evaluation. The second sub-aim is concerned with the quantification of performance, how can one know if a tweak in the design leads to an improvement or if one approach is better than another. The third sub-aim deals with the research needed to understand the limitations of a thigh-worn activPAL3 and to determine whether the main aim can be achieved through analysis of data collected with this device. The fourth and fifth aims combined serve to address the limited evidence on which to base further research and development by closing the feedback loop which has been lacking following previous real-world tests of wearable fall detection performance.

Chapter 2 focusses on why fall detection is needed and the contribution this technology could make. Chapter 3 focusses on the previous approaches to fall detection and culminates in a statement on the current state-of-the-art and a proposal for how fall detection research should be conducted. Therefore, through a review of the literature, Chapter 3 addresses the first sub-aim: to formulate a new framework for the development of fall detection technology. The review identified that there has been a focus on testing fall detection performance and a lack of analysis to understand how performance could be improved. Therefore, to break away from an approach of trial and error, the proposed framework closes the feedback loop so that each test informs further research and development. Accordingly, the fifth sub-aim becomes: to conduct an analysis of real-world fall data to (1) develop an understanding of why existing wearable fall detection technology has not achieved an acceptable level of performance, and (2) to identify characteristics which are unique to falls and could be used to improve performance.

Chapter 4 addresses the second sub-aim through a systematic review of the methods used to evaluate fall detection performance using real-world data. This was the first-ever review of how fall detection performance can be quantified and a more robust approach was proposed based on the findings. The key findings were: (1) the approaches to quantifying performance were inconsistent and many studies used measures which provided limited representation of performance and (2) the sample of falls was generally small and the study populations were diverse, making a comparison between the datasets, and thus results, difficult. Based on this review it did not appear plausible to systematically compare the performance of existing approaches to fall detection and to identify which is best. To address the key issues, it was proposed that larger, shared datasets are needed and that performance is quantified in terms of sensitivity and precision.

It was clear, from the review of previous approaches (Chapter 3), that the focus must be on the real-world and thus, a real-world dataset of falls and activities of daily living would be required to achieve the main aim. It was also clear that the collection of such a dataset represented a substantial challenge and preparatory work was required to ensure the maximum value could be gained from the data. The device selected to collect the real-world dataset was a thigh-worn activPAL3™ due to its common use in studies which have monitored the activity of older adults twenty-four seven. However, there were two unknowns, firstly, fall-related posture classification with a thigh-worn device had never been investigated before and so it was unknown whether the postures before and after a fall could be classified, and secondly, it was unknown if the sensor's range of ± 2 g was sufficient. Hence, a pilot study (Chapter 5) was conducted to test the activPAL3 device as an instrument to record fall signals (sub-aim three). The objective of the pilot study was to record posture and simulated fall data so that: (1) algorithms for the classification of posture before and after a fall could be developed and tested, and (2) the occurrence of clipping in signals recorded by an activPAL3 during a fall could be assessed.

Following the pilot study it was deemed that, on balance, the activPAL3 device was suitable for the collection of a real-world fall dataset. Accordingly, Chapter 6 provides details of a project to record real-world falls and activities of daily living from residents of care homes in the UK using the activPAL3 device. This project addresses the fourth sub-aim, to record a real-world dataset comparable to the largest used in previous studies. Over two years a total of 1,919 days of recordings were collected with forty-two participants across seventeen care homes. Chapter six also details, and provides full results of, the process by which twenty fall signals were identified within the recorded data based on the fall reports provided by the care homes.

Chapter 7 addresses the fifth sub-aim through the most comprehensive analysis of real-world falls to date. The research presented in this chapter utilises the posture classification algorithms developed in Chapter 5 and the data collected in Chapter 6. This study includes many world firsts, including, but not limited to, (1) the extraction and comparison of a specific subgroup of falls and ADL using posture analysis, (2) analysis of the interaction between features of fall and ADL signals, and (3) the investigation of multiple impacts for fall detection. In addition, this study includes an analysis of features common to previous wearable fall detection approaches and provides valuable insight into why these have not yielded acceptable performance.

The final chapter (8) provides a summary of the research presented in this thesis, highlights the key findings and makes recommendations for further research.

Chapter 2

Why Fall Detection Is Needed

2.1 Falls: A Global Healthcare Challenge

Falls in older adults pose a significant challenge to healthcare and wider society; they have previously been described as one of the ‘geriatric giants’, the main ailments associated with ageing [22]. The scale and cost of falls is substantial [23] and expected to grow in the coming decades due to population ageing [24]. Without intervention, the costs associated with falls will rise, with an ever-increasing impact on healthcare [1].

This section aims to: (1) describe what constitutes a fall through a review of definitions, (2) discuss the incidence of falls and the associated costs to society, and (3) examine the physical and psychological consequences of falls.

2.1.1 Fall Definitions

Many definitions of falls exist in the literature. The Kellogg International Work Group provided an early definition of a fall as:

> “An event which results in a person coming to rest inadvertently on the ground or other lower level and other than as a consequence of the following: sustaining a violent blow, loss of consciousness, sudden onset of paralysis, as in a stroke, an epileptic seizure” [25].

This is a suitable definition for studying falls due to sensorimotor impairment and loss of balance but discounts those due to cardiovascular health i.e. syncope [4]; therefore a broader definition is needed. More recently the FARSEEING consortium, a group of experts from a range of fall-related professions, provided a consensus definition of a fall as:

> "An unexpected event in which the person comes to rest on the ground, floor or lower level" [26].

This definition encompasses all types of falls, with no restrictions on the cause and is, therefore, better suited to studying all types of fall.

2.1.2 Fall Incidence

Gauging the true frequency at which older adults fall is challenging given that falls are often not reported, especially when no injury occurs. Estimates suggest that about thirty percent of persons over the age of sixty-five fall at least once each year [27–30] and the proportion rises to around forty-five percent for those over eighty [27]. The risk of falls is higher for older adults living in long-term care (LTC) due to their frailty and other predisposing factors. Estimates suggest the rate of falls is two to three times higher in LTC compared to community settings [31,32]. In hospitals, the incidence of falls varies across departments. In geriatric rehabilitation wards, the incidence is estimated to be 3.4 falls per bed annually and in psychogeriatric wards, the incidence is estimated to be 6.2 falls per bed annually [33].

The main issue is not the high incidence of falls alone, but the combination of high incidence and elevated risk of injury. Indeed, it has been found that the risk of sustaining a fall-related injury increases exponentially with age [34]. This is due to age-related decline (e.g. balance impairment and slowed reflexes) [35] and higher prevalence of other medical conditions (e.g. osteoporosis and sarcopenia) [36]. Of those who fall, an estimated twenty percent will sustain serious injuries requiring medical attention, half of which will include a bone fracture [27,28].

Without intervention, both the frequency of falls and the total number of fall-related injuries is set to increase due to population ageing. Population ageing is a phenomenon taking place throughout the world, whereby older persons are becoming a proportionally larger share of the total population [37]. By 2050, the number of people aged sixty years or over is expected to reach two billion; more than double the number in 2013. The number of people aged eighty or over is growing even faster, expected to more than triple by 2050 [24].

2.1.3 Consequences for the Individual

2.1.3.1 Physical Consequences

Both the incidence and severity of consequences from falls increase with age [34]. Recovery following a fall is highly correlated with physical capability prior to the fall [38]. Therefore, when the oldest and most frail fall the chances of a full recovery are slim and the impact on their health is likely to be long-lasting, if not permanent. Indeed, research has shown that falling is the leading cause of death in people over seventy-five years of age [39].

Falls which result in a fragility fracture, defined as “a fracture caused by forces equivalent to a fall from standing height or less”, are of particular concern [23]. Fragility fractures account for almost sixty percent of fall-related injuries, superficial injuries account for twenty-one percent and head injuries nine percent [40]. The most frequent fragility fractures are to the hip (twenty-eight percent) and the wrist (twenty percent). Due to protective responses, wrist fractures are the most common in fallers under the age of seventy-five, however, in fallers over seventy-five hip fractures become more common as their reactions slow [41]. Of those who suffer a hip fracture, up to ninety percent never regain their previous level of mobility and independence [42]. There is also a strong association between fragility fractures and decreased life expectancy; following a fragility fracture of the hip, about one in ten die within a month and one in three die within one year [23].

Even when a fall does not directly cause injury, the health of the faller can be negatively impacted. Tinetti et al. [2] found that forty-seven percent of uninjured fallers were unable to get up without help, for injured fallers the proportion will be higher. In fallers over the age of ninety, eighty percent cannot get up after a fall and thirty percent remain on the floor for over an hour [3]. If help is not available, the inability to get up leads to a ‘long-lie’ where the faller remains on the ground for an extended period.

In twenty percent of fall-related hospital admissions, long-lies are reported [43]. Long-lies are most common and most severe for falls suffered by independent, community-dwelling older adults. In hospitals and LTC, long-lies are not expected to be common due to frequent monitoring. The time spent isolated on the floor often leads to dehydration, pressure sores, pneumonia, hypothermia and a fear of falling [4–6]. The impact of a long-lie on a faller's health can be severe and many older adults do not fully recover following a long-lie. Wild et al. [44] found that half of those who lie on the floor for more than one hour die within six months.

2.1.3.2 Psychological Consequences

Falls can have severe consequences even when no serious injury occurs. In older adults who have fallen the fear of falling and post-fall anxiety result in a loss of self-confidence and self-imposed restriction of activities [45,46]. A fear of falling does not only occur following a fall, even those who have not had an injurious fall may still be fearful [46]. Estimates suggest that between twenty-five and fifty percent of older adults are fearful of falling and half of these will limit their activities as a result [47,48].

The fear of falling could be more detrimental to an older adult's quality of life than a fall or fracture, and this is largely due to a restriction of activity leading to a reduction in physical ability [49]. Severe activity restriction induced by a fear of falling is an independent predictor of accelerated decline in physical ability and can increase the risk of falling [46,50]. It has been reported that self-imposed activity restrictions often contribute to nursing home admission [51,52]. These findings suggest that although moving less may initially reduce the risk of falling, the detrimental effects on mobility may outweigh any benefit and might lead to increased falls in the future.

In addition to the effect on mobility, the fear of falling and the associated activity restriction can affect mental health. Avoidance behaviours and fear-related anxiety can result in social isolation and subsequently lead to depression [53]. It could also be that depression leads to activity restriction since depression is an independent predictor of fall risk [54,55]. The relationship between the fear of falling, mental health, activity restriction and fall risk is complex and causality has not been demonstrated. However, a fear of falling is detrimental to both the physical and mental health of older adults [46].

2.1.4 Financial Costs

Calculating the total cost to society of falls is challenging due to the number of factors which need to be considered. Many older adults are engaged in activities which benefit society such as volunteering in their community, caring for their spouse or providing family childcare. Those who suffer an injurious fall will need to take a break from their usual activities and may never regain the mobility needed to resume them. It is comparatively straightforward to estimate the direct healthcare costs, however, one cannot easily calculate the cost of a lost contribution to society. Due to a lack of research into the wider costs to society, the following sections discuss only the healthcare costs associated with falls in the UK and worldwide.

2.1.4.1 United Kingdom

In 2003, Scuffham et al. [56] published a report on the cost of falls in the UK, to the author's knowledge this is the most recent published study of its kind. Scuffham found that in 1999 falls cost the NHS and social services £981 million. Of these costs, sixty-six percent were due to falls in those over seventy-five years of age. Most of the costs were for care, forty-nine percent of costs were for hospital inpatient admissions and forty-one percent for long term care. The number of fall-related A&E attendances and hospital admissions were 647,721 and 204,424 respectively.

Current costs are expected to be significantly higher given inflation and population growth. According to the office for national statistics prices have increased by forty-five percent between 1999 and 2017 [57] and the number of people over sixty-five has risen by twenty-eight percent [58]. Based on inflation alone the cost of falls in 2017 would be approximately £1.43 billion; when accounting for population growth the cost rises to approximately £1.82 billion. It should be noted that estimating the increase in costs based on population growth and inflation is not robust, therefore the approximation of £1.82 billion is a very rough estimate; without a new study, it is not possible to get an accurate estimate of costs. Given the last comprehensive analysis of the cost of falls in the UK was conducted two decades ago, there is a clear lack of up to date information and a need for an update to the work carried out by Scuffham et al. [56].

2.1.4.2 Worldwide

There have been two systematic reviews on the cost of older adult falls and their findings remain the leading source for worldwide estimates of fall-related healthcare costs. Davis et al. [59] found that the mean cost was US$3,476 per faller, US$10,749 per injurious fall and US$26,483 per fall requiring hospitalization (at 2008 prices). Heinrich et al. [60] found that between 0.85 and 1.5 percent of total healthcare spending was fall-related. This equated to between 0.07 and 0.20 percent of gross domestic product and between US$113 and US$547 per citizen annually at 2006 prices. Heinrich et al. [60] further found that the mean cost per faller ranged from US$2,044 to US$25,955, the mean cost per fall ranged from US$1,059 to US$10,913 and the mean cost per fall-related hospitalisation ranged from US$5,654 to US$42,840 (at 2006 prices). More studies have been conducted into the cost of falls in the USA than other nations [59,60]. The most recent estimate places the cost of falls to healthcare providers in the USA during 2015 alone at US$50 billion [61].

2.2 Circumstances and Causes of Falls

Falls are hugely variable and occur as the result of a host of contributing factors. These factors can be categorised as internal or external. Internal factors include anything specific to the faller such as reduced balance or visual impairment. External factors include anything circumstantial such as a wet floor or a distraction causing someone to turn suddenly. The interplay between these factors creates the specific circumstances for a fall to occur and therefore provides a useful understanding for preventing further falls.

An understanding of the circumstances and causes of falls is crucial to understand how to manage them (Section 2.3) and it is in the management of falls where fall detection can contribute. Accordingly, this section aims to provide an overview of the circumstances and causes of falls. This section first reviews the internal factors which contribute to elevated fall risk and risk of injury in the event of a fall. Next, the challenges in identifying the circumstances of falls are discussed and a summary of the common circumstances in which falls occur is presented.

2.2.1 Internal Factors Which Increase Fall Risk

The causes of falls are complex and there are many factors which are associated with an increased risk of falling. In a systematic review of falls in nursing homes, Rubenstein et al. [31] identified that the most common causes of falls were gait and balance disorders, muscle weakness, dizziness, confusion, visual impairment, postural hypotension and the use of sedating and psychoactive medications. Deandrea et al. [62,63] conducted two systematic reviews and meta-analyses, one focused on community-dwelling older adults and one on residents of nursing homes and hospital patients. They found that the factors most strongly associated with falls were a history of falls, gait problems, walking aid use, vertigo or dizziness, Parkinson's disease, the use of antiepileptic medications, cognitive impairment and visual impairment. The findings of Rubenstein et al. [31] and Deandrea et al. [62,63] are broadly similar and the main factors are interlinked, for example, gait problems could be a symptom of poor balance, muscle weakness or impaired motor control.

It should be noted that many of the factors identified are symptoms of underlying conditions. Although these factors are useful in understanding why older adults fall, fall prevention interventions should consider the underlying conditions rather than their symptoms. There are a host of factors which can cause gait and balance problems [64]. Neurological conditions such as Parkinson's disease and stroke can affect motor control and other long-term conditions such as arthritis can restrict movement and cause pain [64]. It is likely that not all gait and balance problems are equally detrimental and therefore more work is needed to identify the specific problems which increase fall risk.

Factors such as confusion or cognitive impairment are also very broad categories, and there are many causes of cognitive impairment such as a stroke or dementia. In addition, the label cognitive impairment does not in itself reveal any detail about the nature of the condition. A cognitive impairment could present as impaired memory, judgement or visual-spatial perception [31,65]. It is currently unclear how the individual sub-factors of cognitive impairment effect fall risk [65].

There is evidence that psychotropic medications increase the risk of falls and the risk increases further if more than one psychotropic medication is taken [66,67]. Further, falls have been associated with the following subclasses of psychotropics: neuroleptics, antidepressants, benzodiazepines and sedatives [66,67]. Olazarán et al. [67] found that the highest risk of falls was associated with the combination of long half-life benzodiazepines, neuroleptics, and other psychotropics. No strong associations have been found between cardiac or analgesic medications and increased fall risk [68]. However, slight associations have been found with digoxin, type IA antiarrhythmic, and diuretic medications [68,69].

There is good evidence that muscle weakness elevates the risk of falling. Moreland et al. [70] conducted a meta-analysis using data from thirteen previously published studies which assessed the relationship between muscle strength and falls. They found that muscle strength was strongly associated with falls and the association was stronger for lower body strength than upper body strength. The muscle weakness which occurs with ageing has been attributed to both a loss of muscle mass and muscle quality and these have also been linked to increased fall risk [71]. There is also considerable evidence that some cardiovascular conditions are associated with falls. Jansen et al. [72] systematically reviewed the literature and found low blood pressure, heart failure, and cardiac arrhythmia increased the risk of falling.

Recent meta-analyses found, rather counter-intuitively, that walking aid use was strongly associated with falls both in nursing homes and community settings [62,63]. It is unlikely that walking aids themselves cause falls if used properly, as they are designed to improve stability by increasing the number of points in contact with the ground. The association between walking aid use and fall risk is in part due to those most at risk of falling being more likely to use a walking aid. Research has also found that the majority of walking aid users who fall do not use their walking aid at the time of the fall [73]. Perhaps this association could also be suggestive of poor walking aid use at the time of the fall, however, instrumentation to study stability when using walking aids has only recently been developed and this is an active area of research [74].

It is important to consider more than just factors which increase the risk of falling; ultimately it is the injuries which occur as a result of falls that present the issue. Therefore, one could argue that the factors which increase the risk of injury in the event of a fall are the most important. It has long been known that comorbidities such as osteoporosis can make a fall dangerous which would otherwise be benign [36]. The combination of slowed reflexes and muscle weakness reduce the ability of older adults to break the fall and may, therefore, lead to higher peak forces [75]. It is difficult to isolate factors beyond the conditions which are known to increase the risk of bone fractures or soft tissue injuries; this is due to the methods used to identify factors associated with falls.

At present, the understanding of the factors which affect fall risk comes from studies which correlate observations with the occurrence of falls or fall-related injuries. Therefore, only an association and not causation can be established. Further, one cannot easily separate factors which contribute to the occurrence of falls from factors which contribute to injuries. Studies have demonstrated an association between falls and numerous broad themes such as gait and balance issues or cognitive impairment. However, the understanding at a deeper level of what specific issues and impairments contribute to falls and how they interact is limited. More research is needed before we truly understand the factors which contribute to older adults' fall risk and risk of fall-related injuries.

2.2.2 Challenges Determining the Circumstances of Falls

The majority of research into the circumstances of falls has relied upon interviews and incident reports [76]. These methods rely on the accuracy of faller and witness accounts which are subject to recall problems, social report bias and recall bias [26,77,78]. In many cases, falls are not witnessed and we are reliant on the recall of the faller themselves [78]. This presents an issue as the recollection of the faller, and therefore the fall report can be inaccurate [79]. These issues are exacerbated when recording falls in patients with cognitive impairment, where recall problems may be even more severe [80].

The challenges associated with using interviews and incident reports to identify the circumstances of falls limits the reliability of the findings from studies which used them. Video analysis of falls is the gold standard as it allows multiple experts to assess each fall in detail, which is not possible with other methods. However, there has been very limited research which has used video footage to identify the circumstances of falls. To the author's knowledge, only two research groups have conducted such work [81,82]. Both studies faced the same limitation, cameras were not placed in private areas.

Estimates suggest that seventy-five percent of falls occur in private areas [76]; however privacy concerns prevent cameras being placed in these areas. Despite the lack of video footage of falls in private areas, studies which have analysed video footage of falls provide invaluable insights into the circumstances of falls. To gain the fullest understanding one must review both the detailed and reliable descriptions of falls based on video and the large scale studies which relied on fall reports. The following sections first discuss the findings from the analysis of fall reports and then the findings of studies which have used video analysis.

2.2.3 Analysis of Reports on the Circumstances of Falls

The literature suggests that for community-dwelling older adults the majority of falls occur in the home; with the living room, bedroom and bathroom reported as the most common locations [83,84]. Outside the home falls most commonly occurred in green spaces (gardens, woods, etc.) followed by steps or stairs [84]. The most common causes of falls were reported to be loss of balance, tripping and slipping [83,84].

Rapp et al. [76] conducted the largest analysis of fall reports to date, they included over 70,000 falls from Bavarian nursing homes. They found that around sixty percent of falls occurred in resident's rooms, thirteen percent occurred in the adjoining bathrooms and twenty percent in communal areas. Of the falls recorded, forty-one percent occurred during transfer (e.g. to or from a chair), thirty-six percent occurred during walking and twenty-three percent were classified as other (either unclassifiable or during another activity such as sitting). Perhaps unsurprisingly, the findings showed that as care need increased fewer falls from walking and more falls during transfers were recorded.

In hospitals, the vast majority of falls occur in patient's rooms (seventy-five percent), and bathrooms are the next most common locations (fifteen percent) [85,86]. Similar to nursing homes, the majority of falls in hospitals occur during walking and transfers [85,86]. A high proportion of falls occur during toileting related activities such as walking to the toilet or reaching for toilet tissue [85]. It has also been found that fallers in hospital who usually use a walking aid, often do not at the time when they fall [85]. This supports the earlier suggestions that a lack of walking aid use at the time of a fall may be a reason for their use being associated with increased fall risk.

2.2.4 Video Analysis of the Circumstances of Falls

In 1990, Holliday et al. [81] analysed video footage of twenty-five falls recorded over fifteen months in the communal areas of a long-term care (LTC) facility. They found that the majority (sixty-eight percent) of falls occurred during walking and falls also occurred during standing (twelve percent), during rising (eight percent), while sitting (eight percent) and while bending over (four percent). The most common points of impact were the hip, the buttocks and the knee (each twenty percent). Other points of impact were the hand (twelve percent), the shoulder (four percent) and the side of the thigh (four percent). Responses to a loss of balance were identified in twenty-two of the falls, the responses included: protective arm extension (fifty-six percent), stepping (forty percent), change in walking pace (twelve percent), grabbing (eight percent) and no response (eight percent).

Holliday et al. [81] also studied the events which followed the fall. In forty percent of the falls, the faller came to rest in a sitting position, in twenty percent the faller was supine, in twelve percent they were on their side, in eight percent they were on their knees and in four percent they were prone. The resting position could not be determined in sixteen percent of the falls. In eighty-two percent of the falls, assistance was needed to help the faller from the floor. The findings of Holliday et al. [81] show that those who fall mostly exhibit a response to try and regain balance and that most falls occur during walking. The identification of impact sites and protective responses could be useful for injury prevention research.

Only recently has further work been conducted which used video footage to objectively assess the sequence of events that leads to a fall [82,87]. Robinovitch et al. [82] used existing CCTV systems to capture video footage of falls from two Canadian LTC facilities over three years. CCTV was available in common areas e.g. dining rooms, lounges and hallways. A total of 227 falls were captured during the study and analysed to identify the cause of imbalance and the activity leading to the fall. The cause of imbalance was categorised as one of the following: incorrect transfer or shift of body weight, trip or stumble, hit or bump, loss of support with an external object, collapse or loss of consciousness, slip, or could not tell. The activity at the time of the fall was categorised as one of the following: walking forward, standing quietly, sitting down or lowering, initiation of walking, getting up or rising, walking backwards or sideways, walking and turning, standing and turning, seated or wheeling in wheelchair, standing and reaching, or could not tell.

The results showed that incorrect shifting of body weight was the most common cause (forty-one percent of falls recorded), with trips and stumbles the second most common (twenty-one percent). Most falls occurred during walking (forty-five percent), standing (twenty-four percent) and sitting down (thirteen percent). Using the same dataset, Yang et al. [87] found only a forty-five percent agreement between the incident report and video footage for the cause of imbalance and the activity at the time of falling. This highlights the importance of using objective measures to assess the causes of falls. These studies provide much-needed insight, however, they were limited to three LTC facilities in Canada and only cover falls in the communal areas. There is still more research needed to fill the gaps in the understanding of the circumstances and causes of falls.

2.2.5 Summary

Many factors have been associated with a risk of falling and a risk of sustaining a fall-related injury. However, there are challenges establishing causation and so the understanding of the direct causes of falls is limited. There are also challenges identifying the circumstances of falls. Fall reports can be inaccurate and video analysis, while more accurate, is limited to certain areas due to privacy concerns [87]. New approaches are needed to objectively and reliably assess the circumstances and causes of falls across all locations.

2.3 The Role of Fall Detection in the Management of Falls

The management of falls is critical to lessen their burden on society and ultimately managing falls means preventing them, and where they have occurred, detecting them promptly. Since resources are finite fall prevention efforts must be focussed on those who will benefit and should target their specific risk factors. Assessments of older adults' fall risk are hence crucial to identify those who would benefit from intervention and which interventions are suitable. Even with accurate fall risk assessments and targeted interventions, falls will still occur. To minimise the consequences of these falls, assistance must be received quickly so that long-lies can be prevented. Therefore, fall alarm systems have an important role to play in the management of falls.

Fall alarm systems are the first area where automatic detection of falls can provide benefit, this is discussed in Section 2.3.1. The automated detection of falls as part of an alarm system removes the need for the user to acknowledge the need for assistance and manually trigger an alarm. The second area where fall detection can contribute to the management of falls is as a tool for fall risk assessment, this is discussed in Section 2.3.2. A third area where fall detection technology could be used is in research into the efficacy of fall risk assessments and fall prevention interventions. The ability to accurately log the occurrence of falls is vital to such research as the occurrence of falls is their main outcome measure. Therefore, if proven to be reliable, fall detection systems could be a more accurate alternative to self-report and care staff reports on the occurrence of falls.

2.3.1 Fall Alarm Systems

Unfortunately, not all falls can be prevented and it is, therefore, important that efforts are made to reduce the consequences of falls. One way in which the severity of the consequences following a fall can be reduced is to ensure assistance is received quickly and long-lies are prevented (see Section 2.1.3.2). Research has shown that the earlier a fall is reported the lower the rate of morbidity and mortality [44,88]. Alarm systems are an obvious way in which family or carers can be alerted to a fall.

Personal Emergency Response Systems (PERS) is a term used to describe a category of alarms which the user activates in an emergency. PERS come in a variety of forms and have been commercially available for many years. The most common types of PERS are pull-cords, fixed (e.g. wall-mounted) push-buttons and wearable push-buttons. PERS can be used for any kind of emergency and most are not designed specifically for falls. A faller's movement may be restricted after a fall, preventing them from getting to a push-button, emergency cord or phone. Therefore, PERS aimed specifically at those with a high risk of falls commonly use a wearable push-button, often in the form of a pendant. In care facilities, PERS usually include an audible alarm to notify staff. In the community, PERS usually include a base station connected to a phone line, so that alerts can be sent to either a service provider, family members or carers.

The UK Department of Health conducted the world's largest study of telemonitoring in the Whole System Demonstration Project [89]. The results showed that if implemented effectively, telemonitoring services can reduce mortality, hospital admissions and time spent in hospital. The use of PERS increases the safety of community-dwelling older adults, allowing them to remain independent and live in their own home for longer [90]. In addition, PERS can also reduce the fear of falling through the knowledge that users can get help if needed [90,91].

Though PERS have a clear benefit to their users, push-button systems are limited by the need for user interaction. Therefore, they can only be effective if the user acknowledges an emergency and has the physical and cognitive capacity to press the button [92]. A further concern is that alarms are not always triggered even when the user can do so [3,93]. Fleming and Brayne [3] found that eighty percent of those who fell when alone and could not get up did not activate their PERS; neither did ninety-seven percent of those who remained on the floor for over an hour. Similarly, Heinbüchner et al. [93] found that eighty-three percent of participants who fell when alone and lay for more than five minutes did not activate their PERS. This may be a result of a false assessment of their condition or simply a reluctance to disturb a service operator [92].

To address the limitations of push-button systems, a second generation of PERS devices have been developed. These newer devices contain sensor technology that automatically detects when a fall occurs. However, the precision of fall detection has not been good enough and adoption has been low [94]. The automatic detection of falls is an active area of research, with a focus on the development of an alarm system (see Chapter 3 for a review of automatic fall detection research). Fall alarms could be viewed as a stepping stone to the use of fall detection and activity monitoring technology in fall prevention research. There is substantial overlap between the technology of fall detection and activity monitoring; after all, a fall is essentially just another activity. Therefore, an automatic fall alarm system will be capable of tracking other movements, this combination would provide a rich dataset for research while providing a valuable service for users.

2.3.2 Fall Risk Assessment

One of the major risk factors for falls is a history of falling (Section 2.2.1), therefore, it is important to be able to reliably record the occurrence of falls. Fall incident reports and interviews are the current methods used to assess a person's fall history, however, these are subject to recall problems and biases (Section 2.2.2). In cases where a fall is not witnessed, no injury occurs and the faller can get up from the floor, there is a high risk that the incident would not be recorded, leading to inaccuracies in a person's fall history. For those who live in the community, the sole method for assessing fall history is self-report, except where a long-lie or injury requiring medical care occurs. These non-injurious falls may seem relatively minor, but knowledge of their occurrence and early intervention could prevent a serious fall.

The ability to detect falls using sensor technology could improve fall risk assessment through the provision of an accurate record of fall history. If this technology could be integrated into wearable activity monitors, such as those which have become popular in recent years, then the automatic recording of falls could become ubiquitous. The data generated by such devices could also be highly valuable for research into fall risk factors and the efficacy of fall prevention interventions. At a basic level, activity monitoring could be used to identify changes in daily activity levels over prolonged periods, which might indicate a decline in mobility and an increased fall risk or vice versa. A long-term record of daily activity and falls would allow any such risk factors to be identified, and potentially allow fall risk assessment using activity monitors.

Activity monitoring technology could also be used to assess specific movements to identify known risk factors such as gait or balance problems. The ability to monitor free-living behaviour could give far greater insights into fall risk than a set of tasks carried out in a clinical setting [95]. A fall risk assessment carried out in a clinical setting only considers one point in time, when typically the person being assessed will try to perform their best. Conversely, activity monitoring allows free-living activity to be tracked over time and can provide insights into movement both when a person is at their best and when they are tired or ill, when fall-risk may be at its highest. In addition, the analysis of sensor data can be automated, therefore clinical expertise is primarily needed to design, rather than to carry out, each assessment, thereby allowing a greater number of assessments to be carried out [95,96].

There are two ways such approaches to fall risk assessment could work in practice: (1) as an assessment prescribed by a clinician, and (2) as a product available to the public. Clinicians could ask patients to wear a device for a short period, for example, a week, to collect a series of measures to support assessment. This approach would be similar to any other assessment such as scans or blood tests. As ever more sensors enter daily life, such as in smartwatches and smartphones, fall detection and fall risk assessment could work in a similar way to how fitness trackers are used currently. Those who are concerned about their risk of falling could simply download an application to add such features to their device. Unlike many older adults today, future generations would already be used to such technology.

Research into the use of sensor technology to assess fall risk has already been carried out, however, there have been issues with the way studies have been conducted. In a review of wearable inertial sensor-based fall risk assessments, Howcroft et al. [95] found issues with the methods of testing. Around one-third of studies compared their tool to existing clinical tests which are known to have limited accuracy (see Appendix A for a review), a further third used a retrospective analysis and so tested the ability to identify those who previously fell rather than those at risk of future falls. Only fifteen percent of studies used a prospective design, which is the recommended method for testing risk assessment tools. The ability to automatically detect falls could facilitate this research by allowing a reliable record of the occurrence of falls to be collected.

Despite the limitations of tests of wearable fall risk assessment tools, the potential of the technology is clear [95]. In early trials, assessments using a waist-worn accelerometer in the laboratory have outperformed common methods of fall risk assessment (see Appendix A for an overview of common fall risk assessments). For example, Marschollek et al. [97] used an accelerometer to assess movement during a timed up and go test and extracted a range of parameters from the signals, including step duration, step length and pelvic sway. The time taken to complete the timed up and go test predicted a fall in the following year with an accuracy of 0.5 (where 1 is perfect accuracy), for the St. Thomas's Risk Assessment Tool in Falling Elderly Inpatients the accuracy was 0.48 and the assessment of a multidisciplinary geriatric care team had an accuracy of 0.55. In comparison, the sensor-based test had an accuracy of 0.7 showing that a comprehensive analysis, using an accelerometer, of a person's ability to stand from a chair, walk and sit back down can assess fall risk more accurately than current methods.

2.3.2.1 Summary

The ability to accurately log the occurrence of falls could provide a great deal of benefit both as a tool for fall risk assessment and as a tool to assess the accuracy of other forms of risk assessment. Current evidence suggests that the use of sensors to assess fall risk is more accurate than the existing methods used. Fall detection combined with the ability to monitor other activities has the potential to revolutionise the assessment of fall risk. The ability to assess fall risk continuously during everyday activities rather than in a clinical setting could provide a more accurate assessment of fall risk. As a history of falls is a major risk factor for further falls, the ability to detect falls using sensors could be an important part of future fall-risk assessment technology.

2.4 Conclusions on Why Fall Detection Is Needed

Falls in older adults represent a global healthcare challenge which needs to be addressed. Falls can result in serious injuries, lead to a decline in health and even death; in the UK alone falls are estimated to cost the NHS £1.82 billion each year. Fall detection has a clear role to play in the management of falls. The ability to automatically detect falls as part of an alarm system would ensure help is received promptly and minimise the occurrence of long-lies. A history of falls is one of the main risk factors for future falls, hence fall detection technology could also be used in the assessment of fall risk.

The combination of activity monitoring technology, fall detection and an alarm system could be valuable for those at risk of falling, their healthcare team and research. The alarm system would ensure assistance is received should a fall occur. Such a system could also identify fall risk factors and inform on changes to fall risk, both of which could be useful to clinical staff. Finally, the data gathered by such a device would be useful to those testing new methods of fall risk assessment or fall prevention interventions; such studies rely on an accurate record of falls. It is clear that if accurate fall detection technology can be developed, it would make a valuable contribution to the management of falls.

Chapter 3

Previous Approaches to Fall Detection

The ability to automatically detect falls would be beneficial, as such, a great deal of research has been done on the topic. Continued advances in technology have resulted in a wide range of hardware which could be used for healthcare applications such as fall detection. Consequently, a wide range of approaches to fall detection have been proposed in the literature. This chapter introduces the methodology that has been used to develop and test fall detection technology, discusses the issues in the field and provides an overview of previously proposed system designs. Lastly, this chapter presents a statement on the current state-of-the-art of fall detection and proposes a new framework for the development of fall detection technology. Thus, through a review of the literature, this chapter addresses the first sub-aim of the research for this thesis, to formulate a new framework for the development of fall detection technology.

3.1 Fall Phase Models

When trying to detect a fall, it is useful to use a model of the phases which make up a fall to characterise what it is that one is trying to detect. Several fall phase models have been presented in the literature [26,98–101]; an example is shown in Figure 3.1. Each model is based on three simple phases: pre-fall, fall and post-fall. The various models divide these phases in different ways and use different terms to name phases which are essentially the same.

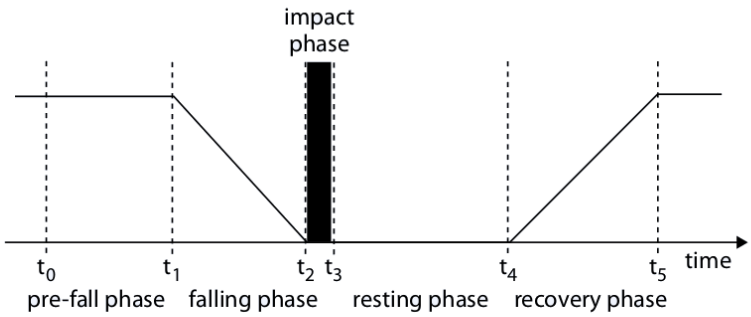


Figure 3.1: The FARSEEING five phase fall model (adapted from: Becker et al. [26]).

In 1993, Hayes et al. [98] proposed that a fall has four distinct phases: instability that results in a loss of balance, descent, impact and post-impact. The separation of the 'fall' phase into descent and impact phases has also been included in most subsequent models. Srinivasan et al. [101] proposed a similar model although it disregards the post-impact phase, only including dynamic changes in gait preceding a fall, free fall and impact. This model does not include anything post-impact, therefore disregards potentially important information such as how much time was spent on the floor and whether the faller was able to stand up unaided. Kangas et al. [99] designed a model for automatic detection of falls using a wearable sensor which used four phases: start of the fall, falling, fall impact, and posture after the fall.

The models discussed so far have only expanded on the fall phase, grouping everything pre and post-fall into single phases. The pre-fall phase is difficult to separate as this is essentially the cause or trigger of the fall. However, it is useful to look closer at what happens post-fall, which often will be the longest phase. Noury et al. [100] was the first to do this with their four-phase model: pre-fall, critical, post-fall and recovery. This model omits the descent and impact phases included in previous models, if these are added in place of Noury's critical phase it gives a five-phase model. The FARSEEING consortium did just that when they proposed a five-phase fall model consisting of pre-fall, falling, impact, resting, and recovery phases (Figure 3.1)[26]. This model was produced by a group of experts from a range of relevant professions and is currently the preeminent fall phase model.

3.2 Fall Detection as a Classification Problem

Fall detection can be viewed as a classification problem and this has been the basis for the methods which have been used for the development and testing of the technology. As a classification problem, the detection of falls is a case of classifying human movement using signals captured through sensors. In the most basic case where falls are the only movement of interest, fall detection is a form of binary classification; each movement is either a fall or not a fall (for a discussion on the challenge in defining a movement see Section 4.4.2). In the wider context of activity monitoring, falls are just one of many movements to classify such as stepping, standing up and sitting down. Fall detection can, therefore, be treated either as binary or multi-class classification, depending on the aim.

Fall detection research has focused on the binary classification case with the aim of developing fall alarms. The fall detection software has, therefore, been designed to process and classify the signals from one or more sensors with near to real-time speed (an alarm raised within a few minutes of a fall occurring). Given that software is used to process the signals, invariably they are digital and thus, a series of readings or samples at a set time interval. Since motion cannot be captured with a single sample, multiple samples are used for fall detection; the number of samples can either be fixed or variable.

Fixed length windows are perhaps the simplest method of processing the sensor signal but also the most artificial. Fixed length windows turn continuous signals into discrete blocks from which features (e.g. peak value) can be extracted and used for classification. Feature extraction is a process of reducing the signal down to a set of meaningful values, thereby simplifying the classifier. Each window is usually processed in the same way making processing time relatively predictable. However, human movements are not of fixed length and so fixed length windows can result in a disconnect between the underlying movement and the signal processing.

An alternative approach to the use of windowing to segment the data followed by rule-based classification of each window, is the continuous analysis of data based on a sequence of threshold-based rules and time-outs or time delays [e.g. 102]. This approach aims to identify key points or phases associated with a fall without the need to pre-define discrete blocks of data. In this approach, the first rule in the sequence is continually applied to the signal; if the threshold is crossed then the next rule is applied either continually with a time limit for crossing the threshold or a time delay and then a single check. If any threshold in the sequence is not crossed, then it is deemed a fall has not occurred and the sequence restarts. Through the identification of key phases of a movement, this method can identify when a fall occurred with greater precision than the windowed approach.

Any approach to fall detection requires knowledge of how fall signals differ from those of other movements. Therefore, data are needed for both falls and activities of daily living (ADL) so that the signals can be compared. Statistical analysis can then be used to develop the rules used to classify the signal as either representative of a fall or another movement. Additional data would be needed for testing, as the same data should not be used to both develop and test a system.

To test fall detection performance a system's predictions as to when falls occurred must be compared with an independent record, such as fall incident reports. There are several measures which can be used to report performance in such tests. Sensitivity and specificity are the most commonly reported in the literature; sensitivity is the proportion of falls which are correctly detected and specificity is the proportion of non-fall events which are correctly ignored. Precision is another important measure, it is the proportion of alarms which are true falls. There are also measures which give an overall score, such as F-measure, the harmonic mean of sensitivity and precision. A full discussion of performance measures can be found in Section 4.3.6 as part of a review on methods of real-world testing.

3.3 Approaches to Data Collection

Data are needed to guide the development of, and to evaluate, fall detection technology. The data required can be divided into two types, namely falls and activities of daily living (ADL). There are two broad approaches to the collection of data for fall detection research, one is lab-based simulations and the other is real-world observation. In lab-based simulations, a predetermined set of activities (e.g. falling, sitting down, walking) are carried out a set number of times in a controlled environment. In real-world observation sensors are used to simply observe participants as they follow their usual daily routine; there is no prescription of activities. Lab-based simulations provide the control needed to record a set number of activities in a short and predictable time scale, whereas the relative rarity of falls during an observation study necessitates long data collections.

Estimates suggest that, due to the rarity of falls, approximately 100,000 days of observation would be needed to capture 100 falls [17]. This estimate was based on the widely reported statistic that a third of older adults fall at least once each year (see Section 2.1.2). Even when only participants identified as having a high fall risk have been included in studies, the number of days of observation that would have been required to capture 100 falls was still in the tens of thousands [19,20]. Another challenge with real-world observation is identifying all the falls which occur so that the data can be accurately labelled (recording which data samples correspond to which activities). The challenges are the same as those for determining the circumstances of falls (see Section 2.2.2), namely, not all falls may be reported and some falls may be reported inaccurately, preventing them from being identified.

The control afforded by a lab study and a set protocol makes it relatively simple to keep track of the falls carried out and label the data. Therefore, the datasets in lab-based studies could be viewed as a more reliable test since there is no risk of falls being mislabelled as ADL, thereby affecting the results. However, if simulated falls are to be used, it is important to consider the validity of this approach and to compare real and simulated falls to understand their differences.

3.4 The Issues with Simulated Falls

Falls are naturally an unexpected and uncontrolled movement and this presents a challenge in recording them. As discussed above, recording real falls is very time-consuming, therefore expensive, and as a result, simulated falls have been far more commonly used [7–10]. However, while easier to record, the signals from simulated falls do not necessarily reflect those of real falls. If a set of simulated falls does not reflect the variation which occurs in real falls, then the results of experiments using the simulated falls will not have high external validity. External validity is the extent to which findings can be generalised to other contexts.

Unlike most human movements, falls are inherently accidental and therefore uncontrolled. Falls are also highly variable, the exact motion depends on the unique set of circumstances, the environment and the reactions of the faller. It is the accidental nature of falls which makes them harder to simulate than other movements. A true simulation of a fall must take control away from the participant, as a deliberate fall is a misnomer given the definition of a fall (see Section 2.1.1). One could imagine developing instruments to artificially initiate specific types of falls, for example, trips, however, doing so for all types of falls could be a burden equal to or greater than recording real falls. Ultimately, real falls would still be required to validate any method for simulating falls, something which would be difficult to do due to the challenges in recording real falls.

3.4.1 Acted Falls

Almost every study which has used simulated falls for fall detection research has relied solely on participants acting falls rather than instrumented methods [9]. In these studies, participants acted falls in a variety of directions, many also asked participants to simulate specific types such as trips, slips and syncope [7,9,10]. Details of the steps taken to maximise the realism are often severely lacking in publications and many studies do not provide any such details. One method which has been employed to improve realism was showing participants videos of real falls [e.g. 103]. However, this method has not been validated and so it remains unknown how it affects the quality of acted falls and if it improves realism.

A major challenge in simulating falls is ensuring the safety of participants; falls can cause serious injuries and subjecting participants to such risks is unethical. For this reason, simulated falls are usually carried out onto a crash mat in an area free from obstacles [7,9,10]; such an environment is different from that in which most real falls occur [76,82]. Be it a corridor, dining room, bedroom or bathroom, there is typically a wall or furniture nearby. A fall could occur as a direct result of interaction with the environment, for example, a trip caused by catching a foot on a piece of furniture or overbalancing when rising from a chair. The motion of the fall could also be influenced by the environment, for example, falling against a wall or reaching for a table to help recover balance. These types of falls are not included in the vast majority of protocols which limits the ecological validity of the simulated fall datasets; ecological validity meaning the degree to which methods approximate the real world.

The safety concerns rule out those most likely to need a fall detector, namely frail older adults, from participating in fall simulations. One factor to consider is that the reactions of older adults are slowed and their muscles weaker compared to younger adults and this affects their response to, and movement during, a fall [104,105]. Compared to an older adult, a young or middle-aged adult would be more able to break a fall, however, the forces required to make them fall, rather than stumble, would also be higher. Only two studies comparing the signals recorded from simulated and real falls have been identified [15,16], and therefore the understanding of the similarities and differences is limited.

Klenk et al. [15] compared signals recorded with a lumbar-worn accelerometer from five real and thirty-six simulated backward falls. Two different methods of simulation were used, in eighteen of the simulated falls participants were asked to fall back as if they were a frail older person, in the other eighteen simulated falls participants tried not to fall when released from a backward lean. Both sets of simulations used a crash mat for safety and were performed by untrained young adults. Klenk et al. [15] found lower variability of the acceleration signal and reduced maximum jerk (the rate of change of acceleration) when acting out a fall as compared to experiencing a real fall. Conversely, when released from a backward lean the maximum jerk was higher than observed in the real falls.

Kangas et al. [16] compared signals recorded with a waist-worn accelerometer from five real and 238 simulated falls; both the real and simulated falls were of various types. Of the five real falls, two were in a forward direction, one was sideways, one was backward and one was a fall out of bed. The simulated falls were acted out by middle-aged participants using a crash mat. Forty samples of each of the following types were recorded: syncope, trip, sit on empty air (simulation of missing a chair), slip, lateral fall and roll out of bed; two of the signals were discarded due to no impact being observable. Kangas et al. [16] found that not all of the real falls had a high pre-impact velocity that they observed in the simulations, this was thought to be due to protective responses in the real falls. A further observation was that there were multiple impacts in the two forward real falls which were not present in the simulations.

These two studies which have compared signals from real and simulated falls both found differences, however, the evidence is severely limited with only ten real falls between the two studies. The findings suggest that results from studies which have tested fall detection technology using simulated falls may be significantly limited in their validity, although the extent of this will be heavily dependant on the features of the signal used. It is, therefore, unlikely that any performance shift between simulated and real falls will be consistent across systems. The lack of research in this area is indicative of the challenge in recording real falls, however, if simulated falls are to be used in fall detection research, then validating the method is required.

Bagala et al. [17] retested thirteen previously published algorithms which had been designed to detect falls in signals recorded with an accelerometer attached to the torso (waist or sternum) and tested using simulated falls and ADL. Twenty-nine real-world fall signals and three days of free-living activity recorded with a lumbar-worn accelerometer were used for the retesting of these algorithms. Bagala et al. [17] found the performance was much lower than had been reported in the tests with simulated falls. Of the algorithms tested the best was originally published by Bourke et al. [106]. The results from simulated falls were a sensitivity of one, a specificity of one, and in a test with fifty-two hours of real-world data, false positives occurred at a rate of 0.6 per day. On the real falls, the sensitivity and specificity were 0.83 and 0.97 respectively with five false positives per day, an unacceptably high rate of false positives which would highly likely be viewed a nuisance by users.

Based on the results presented by Bagala et al. [17], it would appear that it is not possible to predict the drop in classifier performance between simulated and real falls as the drop was highly variable. The worst performance drops were observed in algorithms first published by Bourke et al. [107] and Kangas et al. [102]. In the original publication, Bourke et al. [107] reported a sensitivity of one and a specificity of 0.91, Bagala et al. [17] found with real falls the algorithm had a sensitivity of one, a specificity of 0.11 and a false positive rate of sixty-four per day. Kangas et al. [102] reported a sensitivity and specificity of 0.97 and one respectively; when Bagala et al. [17] retested the algorithm the sensitivity and specificity dropped to 0.14 and 0.92 respectively with a false positive rate of five per day. This highly variable drop in performance between simulated and real falls is indicative of poor external validity and makes it very difficult to establish whether an approach shows potential based on results from tests with simulations.

3.4.2 Artificially Initiated Falls

Only two research group have been identified which used apparatus to artificially initiate falls to develop and test fall detection technology. Nyan et al. [108] included two types of falls in their study: slips and fainting. A pneumatically actuated moveable platform was used to simulate a slip, participants stood on the platform which then rapidly moved forward and caused a backwards fall onto a crash mat. No research has been published which validated this method of initiating trips or which compared the results of testing with this method to the results of testing with real falls. To simulate fainting, Nyan et al. [108] relied on the acting approach, they asked participants to relax their body and drop onto the crash mat; fainting is one example of a fall which would be especially challenging to initiate artificially in an ethical manner as the cause is not mechanical, as is the case for other fall types.

Aziz et al. [103] tested a series of fall detection algorithms using signals recorded with an array of wearable accelerometers during simulations which included both acted falls (n=120) and artificially initiated falls (n=90). Slips were initiated by rapidly translating a carpet on which participants were standing, trips were initiated by pulling taut a tether attached to participants' ankle as they walked, and "hit or bump" type falls were initiated via the investigator applying a sideways force to participants' torso. Not all falls could be artificially initiated, so other fall types simulated were simply acted by participants, these included falls due to a misstep, when rising from a chair, due to incorrect shifting of body weight and due to loss of consciousness. To improve the realism of the acted falls, participants were shown videos of real falls and instructed to fall in a similar manner.

As part of the study, Aziz et al. [103] retested a set of five previously published algorithms, all of which were also tested by Bagala et al. [17]. All algorithms retested showed a drop in performance compared to the original results, as was found by Bagala et al. [17]. The algorithm first published by Bourke et al. [106] showed the greatest drop in sensitivity, a surprising finding given it was the best performing in the tests by Bagala et al. [17]. The performance dropped from a sensitivity and specificity of one in the original test, to a sensitivity of 0.7 and specificity of 0.99 when tested by Aziz et al. [103]. The greatest drop in sensitivity was observed in the acted falls (0.59) rather than the artificially initiated falls (0.83), suggesting an issue with repeatability rather than an effect of artificially initiating falls.

The best performing of the retested algorithms was first published by Kangas et al. [102], conversely, this algorithm was one of the poorest performers in the tests by Bagala et al. [17]. The original results were a sensitivity and specificity of 0.76 and one respectively, Bagala et al. [17] reported 0.31 and 0.97 respectively and Aziz et al. [103] reported 0.94 and 0.94 respectively. The results of Aziz et al. [103] did not reveal any difference in performance between the acted and artificially initiated falls (sensitivity of 0.93 and 0.94 respectively). These findings suggest there may be a serious issue with repeatability; in addition to a lack of transfer to the real-world, there is a lack of transfer between simulated fall datasets. The difference in results between the original publications and the work by Aziz et al. [103] is up to thirty percent, more than enough to mask real differences in performance. It should be noted, however, that although the available evidence points to issues with repeatability the research on this is limited to five algorithms retested twice and further work is needed.

As part of their study, Aziz et al. [103] tested a series of machine learning algorithms, the best of which, a Support Vector Machine (SVM), was then tested using a set of real falls [109]. While not the focus of their research, comparison of the results allows one to assess the transfer of performance between their unique method of simulating falls and real falls. In the first study, the model was trained on half of the simulated dataset (falls and ADL) and tested on the other half, whereas in the second study the model was trained on all the simulated data and tested on the real-world data. When tested on the simulated data the SVM achieved both a sensitivity and specificity of 0.96, on the real data it achieved a sensitivity of 0.8 and a specificity of 0.99, equating to 2.2 false positives per day. The high specificity presented by Aziz et al. [109] can be explained by the method used to divide the non-fall data; each hour of recording was divided into 2.5 second windows with a 1.5 second overlap, giving approximately 86,400 events per day, the majority of which would be signals from sitting or lying and highly unlikely to look like a fall. As was found by Bagala et al. [17], there is a substantial drop in sensitivity between the simulated and real datasets suggesting poor external validity.

3.4.3 Summary

There has been a lack of research assessing the validity of simulated falls for the development and evaluation of fall detection technology. The research to date suggests there are substantial differences between the signals from a set of simulated falls and a set of real falls. Due to this, performance results do not transfer from simulation studies to the real-world data. In addition to the lack of transfer between simulations and the real-world, the limited evidence available suggests issues with repeatability of simulated falls, as when algorithms were retested on new data the results were significantly different. Due to the intricacies of how systems identify fall signals and the lack of research in the area, the shift in performance is unpredictable and it is therefore challenging to evaluate performance based on tests with simulations.

Even though a wide range of sensors have been used in fall detection research with simulated falls, only the validity of simulated falls for accelerometer data has been studied. It is, therefore unknown if the use of simulated falls is a valid approach to test systems using other sensors; repeatability and the transfer to the real-world remain unquantified. Given the findings of the studies using accelerometers, one could reasonably assume that issues are likely. The gaps in the research make it practically impossible to interpret the results from tests of systems and to make predictions of real-world performance. Based on the major issues with simulated falls which have been found, studies using real-world data should be the focus of efforts to understand the current state-of-the-art and to gather evidence to guide further development.

3.5 Overview of System Design

Given the discussions above, this section is limited to a description of the fall detection approaches which have been presented in the literature, rather than a discussion of which perform best, and where further development should be focused. Fall detection systems can be categorised into wearable and non-wearable based on their design. The sub-sections which follow first provide an overview of the classifier design, then provide an overview of wearable and non-wearable system designs.

3.5.1 Classification Techniques

A classification technique is a method of assembling a set of rules which can derive a classification for input data. The input data usually consists of a set of features extracted from the raw data gathered from the sensory hardware. Features are quantifiable properties which can be either: (1) real values e.g. the velocity of an object, (2) integer values e.g. the number of impacts, (3) ordinal e.g. fast, medium or slow walking speed or (4) categorical e.g. posture classification output from another classifier. The extraction of these features requires a stage of pre-processing, specific to the collected data and the features to be extracted from it. This section aims to provide an overview of methods to create a classifier based on a set of suitable features, the sections which follow provide an overview of the features which have been extracted from the signals of the commonly used sensors.

The development of a classifier requires expert knowledge of the problem to engineer a set of features which can be used for classification. The combination of features creates a multidimensional feature space and each data sample fits somewhere within this. The job of a classifier is to map areas of the feature space to the output classifications and there are many ways in which this can be done. There are two main approaches to classification which have been used in fall detection, the first is simple combinations of thresholds, the second is supervised machine learning.

Many of the previous approaches to fall detection, especially those presented in earlier publications, have been based on simple combinations of thresholds to classify the sensor signals as either representative of a fall or not a fall [e.g. 17,102,106]. Thresholds are a method of deriving a binary value from a real, integer or ordinal value and are therefore a form of feature engineering. If all features are binary i.e. threshold-based, then a classifier can be written using the boolean operators AND, OR and NOT. The most common method of combining thresholds is the AND operator, where the output is "fall" if all thresholds are crossed, thus each additional threshold acts to exclude an area of the feature space. A typical example of a classifier which uses a simple combination of thresholds is "fall = high velocity AND high impact AND horizontal posture", where thresholds on the sensor signals are used to determine whether the velocity and impact are high and the posture is horizontal [106].

Statistical techniques can be used to develop more sophisticated classifiers based on patterns in the underlying data; the use of statistical models and algorithms for tasks such as classification is known as machine learning. The aspect of machine learning most relevant to fall detection is supervised learning; in this form, example labelled data are used to train the classifier. There are many algorithms which can be used for supervised learning, each of which has parameters that can be used to tweak the learning process. An example which has been commonly used is the Support Vector Machine (SVM) [12,13], an SVM uses one or more hyperplanes to divide the feature space and each section is assigned a classification. Hyperplanes are located such that the distance to the nearest training sample on each side (which are of different classifications) is maximised. Discussion of the specifics of each machine learning algorithm is beyond the scope of this chapter.

3.5.2 Wearable Systems

Advancements in microelectromechanical systems have led to very small, low-cost sensors which have allowed the development of wearable devices suitable for unobtrusive monitoring over extended periods. As wearable devices move with the user, there is only one restriction as to where they can be used, namely, some form of wireless connection is required to send an alert in the event of a fall. Currently, the portability of devices introduces reliance on battery power and the associated requirement to recharge; current devices cannot recharge whilst in use, leading to gaps in the monitoring period. However, technological development is likely to increase the time between charges, reduce recharging time and potentially could allow charging from movement or body heat whilst in use.

The greatest issue with wearable devices is that the user must both want and remember to wear the device. As users interact directly with wearable devices, their views on the design need to be considered. However, the desires of users must be balanced with the accuracy of fall detection. Without satisfactory sensitivity and false alarm rates, users would be unlikely to trust the device and may cease to use it. In addition, without both high sensitivity and high precision, applications in research such as tracking the occurrence of falls to assess a fall prevention intervention, would be severely limited. To this end, the majority of research on wearable fall detection technology has focused on the development of prototypes and testing of performance rather than establishing users' views so that the design can be fine-tuned.

The need to remember to wear the device makes wearable devices most suitable for those without cognitive impairment. The ability to provide monitoring wherever the wearer goes makes wearable devices particularity suited to those with good mobility and who can live independently. Such individuals may present a lower risk of falls and, therefore, one may assume reduced benefit from monitoring. However, tracking falls and other physical activity in these individuals could yield a critical understanding of how fall risk and injury progress over time and how both can be minimised. Thus, wearable devices have an important role to play in fall detection and fall prevention research. Further, technological developments may reduce or remove their current limitations.

By far the most common sensors used are accelerometers, with gyroscopes a distant second, typically used in combination with accelerometers [8]. Due to both the common use of accelerometers for fall detection and that research on fall detection began with accelerometers, more detail is provided on them in this section than any other sensor. Accelerometers measure linear acceleration and provide data on the orientation of the device with respect to gravity and its movement through space. Gyroscopes measure angular velocity and can be used to estimate changes in orientation. Triaxial devices (those which record in three directions) are most common, generally uniaxial or biaxial devices were only used in early research [8]. The sections which follow provide an overview of the signal processing and feature extraction techniques used for fall detection with wearable sensors.

3.5.2.1 Accelerometers

Accelerometers measure acceleration which can be reported in units of g (multiples of the acceleration due to gravity) or meters per second squared. In the design of an accelerometer-based device, there are two aspects which affect the signal, these are the sampling frequency and the measurement range. There is a trade-off between sampling frequency and power consumption as well as data storage capacity and data processing requirements [110]; thus low sampling frequencies are preferable if fall detection accuracy is not impaired. Studies have used accelerometers with sample frequencies between 6 Hz and 1000 Hz and measurement ranges between ± 2 g and ± 16 g [8]. The optimal sample frequency and range have not been determined and will depend heavily on the signal features used.

Impact and Free-Fall

A typical example of a fall signal is shown in Figure 3.2, this signal is the resultant acceleration vector ($\boldsymbol{a}_r$) from an acted fall. The resultant acceleration can be calculated using Equation 3.1 from the signals recorded with a triaxial accelerometer ($\boldsymbol{a}_x, \boldsymbol{a}_y, \boldsymbol{a}_z$). The majority of previous development has been based on the detection of a spike in the signal which is indicative of an impact [7,8,10]. The trough in the resultant signal which precedes the impact spike is associated with free-fall; detection of this feature has often been used in combination with impact [7,8,10]. It should be noted that unlike an object falling, when a person falls there is typically contact with the ground, furniture or a wall and therefore, a period of true free-fall is rare. Impact and free-fall are both undoubtedly associated with the occurrence of a fall and are, perhaps, the most intuitive features to identify in the signal. For this reason, these features were promoted in early publications [e.g. 107] and they have remained prominent.

$$\text{Resultant Acceleration } (\boldsymbol{a}_r) = \sqrt{\boldsymbol{a}_x{}^2 + \boldsymbol{a}_y{}^2 + \boldsymbol{a}_z{}^2} \tag{3.1}$$

Early studies found that the observed peak in the resultant signals recorded with accelerometers attached to the waist, thigh and head were typically much higher in acted

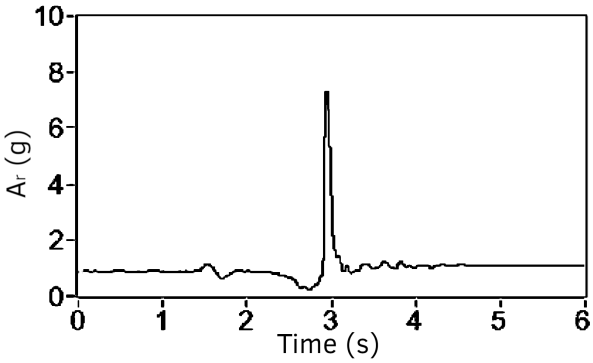


Figure 3.2: Example accelerometer signal recorded during an acted fall (adapted from Kangas et al. [102]). The plot shows the resultant acceleration ($\boldsymbol{a}_r$) of the signals recorded by a triaxial accelerometer during the fall. Data were collected using a device attached to the waist, the sensor had a range of ±12 g and a sampling frequency of 400 Hz.

falls compared to activities of daily living (ADL) (one to three g for ADL versus two to ten g for falls) [107,111–113]. Based on their findings it was proposed that simple thresholds could be used to distinguish the impact associated with falls from the signals of other activities. However, there was overlap between falls and ADL in the peak resultant values observed. Therefore, impact assessment alone could not fully distinguish between falls and ADL, and so other features were examined in search of a combination which could better differentiate falls and ADL.

Bourke et al. [107] proposed the minimum resultant value as a method to detect the presence of the trough in the signal. Alone, the minimum resultant value was less able to separate falls from ADL compared to the peak value, however, the combination provides an expanded characterisation of the signal which may help classify the fall signals. The combination of thresholds for the minimum and peak resultant values has been used in a number of studies [e.g. 16,99,106,114,115], typically with other features to improve classification. These features have been used to generate further features, for example, Kangas et al. [113] proposed the measurement of time between the start of the fall and impact, where the start was the nadir (minimum value) of the trough in the resultant acceleration and impact was the peak.

Accelerometer Orientation

When static a triaxial accelerometer measures the three components of the effect of gravity acting on its measurement mass, which allows the orientation of the sensor relative to the gravity vector to be calculated. However, when in motion the total set of inertial and gravitational forces acting on the measurement mass is unknown, therefore some assumptions are made to estimate orientation. For example, the signal is typically low-pass filtered or averaged in an attempt to remove the part of the signal due to motion. The orientation of an accelerometer, and thus the orientation of the body-part to which it is attached, can be used to infer posture. One would expect posture to change during a fall, for example from standing to lying, where both the torso and thigh would go from upright to horizontal. For calculations of orientation, the axes labels are important, Figure 3.3 shows the labels used for the equations in this section.

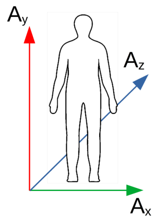


Figure 3.3: Orientation of accelerometer axes relative to the wearer when standing.

Chen et al. [111] and Brown [116] were the first to propose the use of orientation in fall detection, both calculated the orientation of a waist-worn accelerometer. Chen et al. [111] calculated the change in angle between one second before and two seconds after impact using Equation 3.2. To isolate the gravity component of the signal, Chen et al. [111] averaged the signals over one second (1.5 - 0.5 s pre and 1.5 - 2.5 s post-impact) and used the average values in the calculation. Brown [116] calculated the angle with respect to gravity twelve seconds after impact using Equation 3.3; a Butterworth second-order low-pass filter was applied prior to calculation of orientation. Sensor orientation based on these equations has continued to be used with torso worn accelerometers [e.g. 20,99,106,117,118]; the orientation of the torso is particularly suited to the detection of lying, a common posture following a fall. To the author's knowledge, the use of accelerometer orientation with other body locations has not been attempted.

$$\text{Orientation Change } (\theta) = \cos^{-1}\left(\frac{\boldsymbol{a}_{x(t1)} \cdot \boldsymbol{a}_{x(t2)} + \boldsymbol{a}_{y(t1)} \cdot \boldsymbol{a}_{y(t2)} + \boldsymbol{a}_{z(t1)} \cdot \boldsymbol{a}_{z(t2)}}{\boldsymbol{a}_{r(t1)} \cdot \boldsymbol{a}_{r(t2)}}\right) \quad (3.2)$$

$$\text{Orientation with respect to gravity } (\theta) = \cos^{-1}\left(\frac{\boldsymbol{a}_y}{\boldsymbol{a}_r}\right) \quad (3.3)$$

Vertical Acceleration

Kangas et al. [113] were the first to propose the use of vertical acceleration for the detection of falls. To calculate vertical acceleration, Kangas et al. [113] used Equation 3.4, where G is the magnitude of the acceleration due to gravity (one g) and $\boldsymbol{a}_{r(Dynamic)}$ is the resultant of the dynamic component of the triaxial accelerometer signals. $\boldsymbol{a}_{r(dynamic)}$ was calculated using Equation 3.1 with high-pass filtered triaxial accelerometer signals; a second-order Butterworth filter with a 0.25 Hz cut-off frequency was used to filter the signals. Kangas et al. [113] did not provide justification for, or validation of, their equation; the equation does not take orientation into account and it would appear to only be valid if the direction of the resultant acceleration is directly towards the ground. Vertical acceleration has been used in further work by the same research group [16,20,99], but has not been adopted by the wider field. In their systems, Kangas et al. used the peak vertical acceleration as a feature to distinguish falls from ADL.

$$\text{Vertical Acceleration } (\boldsymbol{a}_v) = \frac{{\boldsymbol{a}_r}^2 - {\boldsymbol{a}_{r(Dynamic)}}^2 - G^2}{2G} \tag{3.4}$$

Velocity

Calculation of velocity from accelerometer data is, arguably, the most challenging transformation of those which have been used in fall detection systems. Acceleration is the rate of change of velocity, thus, change in velocity can be calculated through integration of an acceleration signal. However, in practice, the calculation of velocity from accelerometer signals is far more complex. The first issue is that any error or noise in the accelerometer measurement is amplified in the calculated velocity and causes substantial drift over time. Absolute velocity is the sum of the initial velocity and the integrated acceleration, thus the further from the initial known velocity the greater the margin of error.

The second issue is the separation of the constant acceleration due to gravity and the effects of inertial forces. The magnitude of the acceleration due to gravity is known, but the relative orientation of the accelerometer is unknown, therefore one cannot simply subtract the gravitational component from each axis. One must either: (1) high-pass filter the signals to remove an estimation of the gravitational component for each axis, or (2) subtract the gravitational component from the resultant acceleration. Neither option is ideal, option one will introduce a potentially very large margin of error due to imperfect removal of the gravitational component. Option two is based on the assumption that the resultant acceleration is towards the ground, the greater the angle from vertical, the greater the error in the velocity estimation [112].

The third issue is the effect of acceleration due to angular rotation, something which is likely to occur during a fall. Rapid rotation of an accelerometer causes acceleration outwards from the centre of rotation (due to the centrifugal force), but not necessarily outward movement since in the context of fall detection the device is secured to the wearer. Therefore, rotation of the accelerometer introduces error in the velocity estimate. Since accelerometers do not measure rotation, accounting for it is not possible without additional sensors e.g. gyroscopes. Despite the challenges, several research groups have devised approaches to calculate velocity for accelerometer-based fall detection systems.

The use of velocity in fall detection was first proposed by Degen et al. [112] for use with a wrist-worn device. Degen et al. [112] proposed two equations to estimate velocity (Equations 3.5, 3.6), in the first, the gravitational component is subtracted from the resultant acceleration prior to integration of the signal, in the second, each accelerometer axis is integrated separately and the integral of the gravitation component subtracted from their root sum of squares. Equation 3.5 is less affected by changes in orientation and rotation of the accelerometer, Equation 3.6 produces a better estimation providing the accelerometer is not rotated during the fall [112]. The likelihood of rotation during a fall limits the value of Equation 3.6, and as a result, Equation 3.5 has been the preferred choice in subsequent research [10]. The calculation of velocity is typically used to establish the peak velocity within a period of time, usually between the point at which the resultant acceleration drops below one g and the following impact spike [e.g. 20,99,106,113,119].

$$\text{Velocity Change } (\Delta \boldsymbol{v}_1) = \int \boldsymbol{a}_r - G \,\mathrm{d}t \tag{3.5}$$

$$\text{Velocity Change } (\Delta \boldsymbol{v}_2) = \sqrt{\left(\int \boldsymbol{a}_x \,\mathrm{d}t\right)^2 + \left(\int \boldsymbol{a}_y \,\mathrm{d}t\right)^2 + \left(\int \boldsymbol{a}_z \,\mathrm{d}t\right)^2} - \int G \,\mathrm{d}t \tag{3.6}$$

3.5.2.2 Gyroscopes

Gyroscopes measure angular velocity ($\boldsymbol{\omega}$), commonly reported in degrees per second. Gyroscopes have a much higher power consumption than accelerometers and therefore are limited in their application by battery life. Hwang et al. [120] was the first to propose the use of gyroscopes for fall detection; they combined an accelerometer and gyroscope in a sternum worn sensor, however, they did not provide details of how these signals were processed. The first gyroscope signal feature presented in the fall detection literature was peak angular velocity, which is indicative of a rapid rotation from a vertical to horizontal posture. Nyan et al. [108] used thresholds on peak angular velocity from three uniaxial gyroscopes for pre-impact fall detection, the sensors were located at the sternum, waist and underarm. Peak angular velocity has continued to be used, albeit with slightly altered signal processing, for example, Bourke and Lyons [119] used the peak of the resultant angular velocity across the frontal and sagittal planes using a biaxial gyroscope.

Angular acceleration can be calculated through differentiation of angular velocity and the change in angle can be calculated through integration. Resultant angular velocity can be calculated using Equation 3.7 where $\boldsymbol{\omega}_p$, $\boldsymbol{\omega}_r$ and $\boldsymbol{\omega}_y$ are the three axes of the gyroscope (pitch, roll and yaw respectively). The peak resultant angular acceleration has been used in several studies [e.g. 121,122]. The resultant change in angle can be calculated using Equation 3.8, thresholds for angle change have been common in systems which include gyroscopes [e.g. 122,123].

$$\text{Resultant Angular Acceleration } (\boldsymbol{\alpha}_r) = \sqrt{\left(\frac{\mathrm{d}\boldsymbol{\omega}_p}{\mathrm{d}t}\right)^2 + \left(\frac{\mathrm{d}\boldsymbol{\omega}_r}{\mathrm{d}t}\right)^2 + \left(\frac{\mathrm{d}\boldsymbol{\omega}_y}{\mathrm{d}t}\right)^2} \tag{3.7}$$

$$\text{Resultant Angle Change } (\Delta\theta_r) = \sqrt{\left(\int \boldsymbol{\omega}_p \,\mathrm{d}t\right)^2 + \left(\int \boldsymbol{\omega}_p \,\mathrm{d}t\right)^2 + \left(\int \boldsymbol{\omega}_p \,\mathrm{d}t\right)^2} \tag{3.8}$$

The combination of a triaxial gyroscope and triaxial accelerometer results in a device with six degrees of freedom (three linear and three angular). An accelerometer can measure orientation when static, but not accurately when in motion, a gyroscope can measure a change in orientation, through the integration of angular velocity, but not absolute orientation. When combined these two sensor types can be used to far better estimate orientation relative to the ground than either can individually. Quaternion filters have been used to estimate orientation and acceleration relative to an inertial reference frame [122,124]. Vertical velocity can then be calculated through the integration of the vertical acceleration signal, this method provides greater precision than calculation from the untransformed accelerometer signals [122,124].

3.5.2.3 Magnetometers

Magnetometers measure the strength of magnetic fields and therefore can be used as an electronic compass. Using the earth's magnetic field, which points north, as a reference, magnetometers can be used to determine orientation in the plane orthogonal to gravity. However, the earth's magnetic field is weak in comparison to magnetic fields generated by other local sources and so the determination of orientation using magnetometers is prone to error. Magnetometers can be combined with accelerometers and gyroscopes to provide a more accurate estimate of orientation than either can individually and this is why they have been used in fall detection systems. The estimation of change in orientation and vertical motion have been common features in wearable fall detection and a magnetometer can increase the accuracy of these estimations, albeit at the expense of power consumption and therefore, battery life; more sensors means greater power draw. The process for combining magnetometer signals with those from accelerometers and gyroscopes is largely the same as for combining just accelerometer and gyroscope signals; the use of a quaternion filter has been a common approach [e.g. 125,126].

3.5.2.4 Atmospheric Pressure Sensors

When one falls their centre of mass moves downwards, therefore, the ability to measure the change in height or altitude could prove useful in fall detection. Air pressure decreases with altitude and so its measurement can be used to estimate the drop associated with a fall. Bianchi et al. [117] pioneered the use of atmospheric air pressure sensors (barometers) for fall detection, their proposed system combined the pressure sensor and an accelerometer in a waist-worn device. The pressure sensor had a resolution of equivalent to approximately ten centimetres at sea level, just enough to determine if the wearer had fallen to the ground. Bianchi et al. [117] calculated change in pressure over four seconds and then normalised by the wearer's height.

3.5.2.5 Hardware Design

The design of fall detection systems is an active area of research and so, naturally, most systems presented in the literature are prototypes and user's perspective on their design has not been established. The priority first and foremost has been on developing a solution with suitable performance, rather than packaging the hardware into a desirable device. There are two aspects which are largely fixed at the prototype stage, these are the number and location of sensors.

The vast majority of proposed systems have used only a single device, as this is thought to be more acceptable to users [8–10]. A system which relies upon multiple devices would be less usable; if the user were to forget to wear one of the devices the systems would not function properly. Fall detection systems must be simple and unobtrusive to facilitate continuous wear; the use of a single, preferably small, device is integral to achieving this. There have been studies which have used multiple sensors, however, these typically aim to identify the location which maximises performance [e.g. 113].

By far the most common choice of location is the waist, the upper torso has also been a common choice [8–10]. The waist is popular for two reasons, (1) it is close to the centre of mass which is thought to be optimal for detecting a movement of the body towards the ground, and (2) the ability to attach a device to a belt is convenient. A wrist-worn device is potentially preferable to users due to familiarity with wrist-worn watches, however, the wrist moves around a great deal during daily activities and is prone to knocks which could be mistaken for an impact due to a fall; the wrist, therefore, presents additional challenges and has been a less common choice [8–10]. The upper torso has been used as it is thought to be a good location for measuring angular velocities and the detection of lying postures.

The commercially available fall detection systems mainly use an accelerometer either worn as a pendant, on the waist or wrist [10]. The devices are typically lightweight (<100 g), less than 100 millimetres in length, 50 millimetres in width and 20 millimetres in-depth and have a battery life ranging from one day to two years. Push buttons are common on commercial devices to allow the user to request assistance for non-fall related reasons or in the event of an undetected fall. A further use of the push-button is to allow the user to cancel an alert in the event of a false positive fall alert.

3.5.2.6 Summary

Since 1998 there have been over 200 published articles on wearable fall detection systems [7–12]. A wide range of approaches have been proposed in the literature, however the central themes of impact, postural change and vertical motion run throughout the field of research. This section has provided an overview of the main sensor types along with the processing of their signals. The vast number of combinations of sensors and signal processing techniques presented in the literature prohibit a complete rundown of approaches, however, the core of the research has been characterised. Through the combination of techniques described in this section, it is possible to arrive at almost any of the previous approaches to wearable fall detection presented in the literature.

3.5.3 Non-Wearable Systems

Non-wearable systems are those which do not travel on one's person, usually, non-wearable systems are installed in fixed positions around the home or a care facility. To be effective non-wearable systems are reliant on the user being inside their measurement range, for example, they cannot monitor a user when out shopping. For this reason, it could be argued that non-wearable fall detectors are most suitable for those who do not frequently go out unaccompanied. Furniture could also block the sensor's view unless their position is carefully considered or multiple sensors are used. Research has suggested that a limited capture area may lead users to feel confined to the known capture space, thereby affecting their daily activities [127], therefore full coverage of a user's living space is highly desirable.

A fixed position is simultaneously the biggest advantage and disadvantage of non-wearable devices; while a fixed position limits the area a system can cover, it also removes the need for user interaction. Naturally, with non-wearable devices the user does not have to remember to wear a device, thereby reducing, if not removing, the problems with user compliance that can occur with wearable sensors. Non-wearable devices can be larger than wearable ones, use wired connections for communication and use mains power, removing the need for charging and reducing the risk of connection problems. Finally, due to monitoring a space rather than a single wearer, non-wearable devices can monitor multiple people, although this also increases the complexity of software required as each person needs to be tracked individually. However, the ability to monitor multiple users with each device could mitigate some of the added cost of the multiple devices required to cover a space, particularly in care facilities. The sub-sections which follow provide an overview of common non-wearable sensors and the associated signal processing.

3.5.3.1 Computer Vision

Computer vision is an active field of research concerned with automatic extraction of information from images or sequences of images (video) to allow computers to understand a scene; this includes three-dimensional analysis using images from multiple sensors. Vision-based systems have been the most common type of non-wearable system, historically video cameras have been the most common choice of sensor [7,9,10]. The Kinect™ device has been a common choice in recent fall detection studies [12], the device combines two cameras, one standard visible light video camera and one infra-red depth-sensing camera. Since 2014, camera-based systems have received less attention in the academic literature, featuring in only two of the twenty most cited articles on fall detection published between 2014 and 2018, conversely, the Kinect device featured in nine of the articles [12].

One potential advantage of camera-based solutions is the possibility of utilising existing camera networks installed in care facilities. However, as discussed in section 2.2.2, there are privacy concerns associated with installing cameras in private areas such as bedrooms and bathrooms, where a high proportion of falls occur. Unless the privacy concerns can be addressed, camera-based systems are likely to miss a large proportion of falls. Since for computer vision applications the images are processed without human interaction, it is possible to preserve privacy, however, appropriate protections will be needed to prevent misuse. To raise an alarm, a fall detection system must have a connection to the outside world, thus it could be hacked and private images stolen.

The processing required for computer vision is arguably the most complex of all the approaches to fall detection. Firstly, a video stream contains more data than other sensor signals such as accelerometers; a triaxial accelerometer produces three signals, by comparison, a video feed typically contains hundreds of thousands, if not millions, of pixels. Secondly, in a normal living space, the observed scene will contain many items and potentially multiple people which may cause interference, for example, occlusion of the user. The identification of a person falling or who has fallen within a busy scene, and to do so independent of lighting conditions, is far from a simple task and there have been a variety of approaches presented in the literature. A full discussion of the intricacies of the feature engineering for each approach is beyond the scope of this section, however, an introduction to two common approaches, namely bounding boxes and measurement of the distance from the floor, are provided below as representative examples.

Shape Tracking via Bounding Boxes

Typically the first step in fall detection using cameras is to identify the people in the scene so that they can be tracked, this is often referred to as foreground extraction. People and their movements account for the vast majority of change in a scene, therefore the static parts make up the background, whereas the parts which change make up the foreground. One option is to record a series of images of the scene with no people present to capture the background and then subtract this from each subsequent image to reveal the foreground [e.g. 128]. While this simple method works in a laboratory test, in the real world background objects get moved as part of daily life, thus a method to continually update the stored background is needed. Motion segmentation techniques can be used to identify the moving parts of the scene so that the background and foreground can be separated [e.g. 129–131]. Further image processing can be used to remove shadows, the effect of changes in illumination and other noise so that only the silhouettes of moving objects remain, which are assumed to be people.

A postural change is a characteristic common to almost all falls, the notable exception being a fall out of bed which may be from lying to lying. Therefore, just as within the field of wearable fall detection, the analysis of posture has been important in computer vision-based fall detection [13,132]. Once people in the scene are identified their movements can be tracked using a bounding box, the smallest box which can contain their entire silhouette. The bounding box provides a simpler, more robust and computationally efficient framework for feature engineering compared to tracking the precise shape of a silhouette [129]; an ellipse can be used as an alternative to a box [e.g. 133]. Limits can be placed on the size of bounding boxes to exclude objects which are just residual noise from imperfect identification of people [e.g. 128]. Features extracted from bounding boxes are typically height, width, aspect ratio and orientation, it is the changes in these parameters over a series of images which are used to identify falls [e.g. 128,129,131].

Measurement of Vertical Motion

Based on the definition of a fall (see Section 2.1.1), there must be a descent of the centre of mass, therefore the ability to measure vertical movement of the body is valuable in fall detection. Early work on computer vision approaches to tracking motion towards the floor used calibrated video cameras [e.g. 134], however, depth cameras such as the Kinect have become far more common as their availability has increased [12,132]. Uncalibrated two-dimensional cameras cannot be used to measure motion as movements appear larger when close to the camera, calibration allows three-dimensional position to be estimated using normal video cameras [134]. The extra information provided by depth cameras allows motion to be tracked with only a single device and also better separation of the foreground from the background, thereby making person identification more accurate [135]. Following person identification, the distance of their central point from the ground can be measured and from this, vertical displacement and velocity calculated. Systems have been designed to detect falls using combinations of thresholds for vertical displacement, vertical velocity and distance from the floor [134–138].

3.5.3.2 Sound and Vibration

Sound and vibration-based fall detection systems aim to detect falls via impact detection, based on the kinetic energy of a faller being transferred to vibrations in the floor and air (sound) upon impact. Vibrations travelling through the floor have been recorded, for fall detection, with both piezoelectric sensors and accelerometers, sound has been recorded with microphones [139]. Spectral analysis has been the predominant basis for feature engineering of sound and vibration-based fall detection systems [139]. The main challenge for this type of system is that sound and vibration is heavily influenced by the construction of the floor [140], thus it is difficult to produce a system which performs in all spaces. Another challenge is filtering other sources of noise and vibration, such as that produced by a television or radio; noisy environments may mask the signal from a fall and may cause false alarms. There are some privacy concerns with the use of microphones as personal conversations could be recorded, therefore appropriate safeguards need to be included in the design of these systems.

3.5.3.3 Radar

The use of radar systems for fall detection is a comparatively new area of research which aims to develop non-wearable fall detection which is not subject to the privacy concerns present with other non-wearable approaches [12]. Radar systems use radio waves to determine the distance and velocity of objects; they emit electromagnetic waves which reflect off objects and are then picked up by a receiver. The most common type of radar used is the Doppler radar, these emit a wave with a set frequency and use the shift in frequency of the reflection to measure the velocity of an object [12,139,141]. Radars are most sensitive to motion in the direction of the emitted waves and least sensitive to perpendicular motion [139], therefore placement is critical. Ceiling mounted Doppler radars have been used to measure vertical motion for fall detection [e.g. 142,143].

3.5.3.4 Summary

There are both benefits and disadvantages of non-wearable approaches to fall detection compared to wearable ones. Their main advantage is that users do not have to remember to wear or charge a device, which makes them particularly suitable for those with cognitive impairment. The main disadvantage of non-wearable approaches is their limited capture area and inability to function wherever the user goes. The complexity of signal processing required for non-wearable approaches has typically been greater than that for wearable approaches, this has made them less viable as a real-time fall detection solution. Continued improvements in computing power and sensor technology have increased their viability and the increase in the volume of research on non-wearable fall detection in recent years reflects this [12]. Historically non-wearable approaches have been affected by privacy concerns surrounding the placement of cameras in private areas, however new approaches such as the use of radar present considerably less risk to privacy.

3.6 Current State-of-the-Art of Fall Detection

Over the last two decades, there has been a great deal of research conducted into fall detection systems and a wide range of sensors and signal processing methods have been tested. The vast majority of testing has used laboratory-based simulations of falls (primarily acting), an approach which the limited evidence available suggests suffers from poor external validity (Section 3.4). Results of tests using simulated falls have been shown not to transfer to real-world contexts, severely limiting the insight which can be gained from this research; when systems perform perfectly in controlled tests but badly in the real-world, further development is hampered. There has been a lack of research into methods of simulating falls which provide higher validity and this has resulted in little improvement in testing methods. Instead, the focus has begun to shift towards real-world data, however, due to the challenges associated with recording real falls this shift has been slow, many groups are still reliant on simulation data and the real-world datasets which have been collected are small [144].

Due to the poor validity of simulated fall studies, understanding of the current state-of-the-art performance can only be gained from the real-world studies. However, there is value in knowledge of the previously proposed approaches when planning further work, even if their true performance remains unknown. Therefore, the following subsections provide a summary of previous approaches to fall detection and a discussion of the available results from real-world testing.

3.6.1 Wearable Versus Non-Wearable

There are a set of common themes which have arisen in the review of previous approaches and apply to both wearable and non-wearable sensors; these common themes are impact, vertical motion and posture change. Although each sensor type may be more suited to the detection of aspects which fall under certain themes, all approaches make measurements which fall into at least one of these themes. The emergence of these themes is perhaps unsurprising given that a fall is an accidental downward movement resulting in a collision with the floor or another surface. Nevertheless, the emergence of these themes highlights the common ground shared across the field of fall detection. To guide future research and development it is important to develop an understanding of how falls and other movements differ and establish the relative importance of each of these themes.

An understanding of the differences between falls and other movements is critical to the development of fall detection technology. While one may have an understanding of what a fall is, this is not enough to be able to isolate them from the vast array of other movements made in everyday life; only through observation of real-life motion and routines can the isolating factors be established. Research in the area could be conducted with any of the sensors used in fall detection; in fact, consideration of evidence produced from studies using different approaches is important to ensure conclusions are valid. With an understanding of how falls are unique, further development can be evidence-based. Without an evidence base on which to make design decisions, trial and error is the only option. Given the current state of the field, sensor choice, be it wearable or non-wearable, and the type of classification algorithm used to combine signal features are both far less important than the identification of features which can effectively discriminate between falls and other movements.

3.6.2 Results of Real-World Evaluation

Research into fall detection using real-world data is at an embryonic stage and there are variations in the methods used to test systems which limit the ability to make robust comparisons between the results. Nevertheless, the studies using real-world data to test fall detection systems provide the only evidence to establish the current state of the art in terms of system performance. Due to the use of different datasets and variations in methods (see Chapter 4), it is not possible to establish which systems are the best performing; one can only establish the range in performance which has been reported as an estimate of the current state of the art. The results presented below were extracted from articles identified through a systematic search of real-world fall detection technology tests (Chapter 4; for details of the search see Table 4.1 and for details of the studies reviewed see Table 4.2).

Reported sensitivities of wearable devices range from 0.14 [17] to 1.0 [17,145–147], precision has ranged from 0.01 [17,18,20,148] to 0.89 [122]. The reported sensitivity of non-wearable systems ranged between 0.19 [149] and 1.0 [142], precision ranged between 0.003 [149] and 0.37 [150]. Generally, those which achieved high sensitivity had a low precision and vice versa, the exception was Bourke et al. [122] who tested twelve variations of combinations of features, the best of which achieved a sensitivity of 0.88 and a precision of 0.87. However, the generalisability of the results presented by Bourke et al. [122] is highly questionable, they used a synthetic oversampling technique to boost the fall samples from 89 to 367 and then used ten-fold cross-validation to train and test decision tree classifiers. Therefore, the test data was not independent of the training data, so the classifier may be overfitted to the training data, as without independent training and testing overfitting cannot be detected.

Two studies tested wearable devices developed by commercial companies, these studies provide insight into the performance of the systems available commercially. Lipsitz et al. [21] tested a pendant fall detection device produced by Royal Philips (Amsterdam, Netherlands); the device used an accelerometer and proprietary signal processing. The study used data collected with sixty-two participants over 9,300 days which contained eighty-nine falls; it is to date the largest real-world study of a wearable fall detection device. Of the eighty-nine falls, seventeen were detected by the device (sensitivity = 0.19), a total of 128 events were detected as falls (precision = 0.13), the F-measure score was 0.16. Chaudhuri et al. [18] conducted a test of an unnamed proprietary wearable fall alarm which contained an accelerometer, gyroscope and magnetometer. A total of 4 falls occurred during the 1,452 days the device was used, one fall was detected (sensitivity = 0.25) and eighty-four alarms were raised (precision = 0.01), the F-measure score was 0.03. Further details of these studies can be found in Table 4.2. Neither of these studies made it clear whether these devices were commercially available or prototypes, however, they are the only real-world studies of devices produced by commercial companies. The results of the studies suggest that the performance of commercially available devices is extremely poor, with both studies finding that the devices failed to detect the majority of falls and made many more false-positive detections than fall detections.

3.6.3 Conclusions

In real-world tests the performance of fall detection technology has been poor, systems have achieved either high sensitivity or high precision, but not both. With only limited independent testing of commercial devices, one cannot be certain of the current level of performance for commercially available systems, however, there is no evidence to suggest that they perform reliably. With low sensitivity, users cannot trust the system to raise an alarm when needed and may discontinue use of the system. With low precision it is more likely that an alarm is a false positive rather than a real fall, this is likely to lead to alarm fatigue in those responding. Alarm fatigue is a desensitisation to alarms leading to slow or no response, it is caused by a high number of false alarms; in medical contexts patient deaths have been attributed to a failure to respond as a result of alarm fatigue [151,152]. For research into the occurrence and causes of falls the current systems remain unusable, their performance is far too poor.

3.7 Proposed Framework for Further Development of Fall Detection Technology

The prevailing approach to developing fall detection technology has been to use simulated falls and then, where possible, to test performance on real-world data [e.g. 19,20,109].

The evidence has shown that simulated data is a poor substitute for real-world data (Section 3.4); we have been able to robustly detect simulated falls for over a decade, but during this time improvements in real-world fall detection have been limited. Due to the challenges in collecting real-world fall data (Section 3.3), relatively few systems have been tested on real-world data (see Chapter 4). Typically, studies have focused on testing classifiers which are in some way novel; only a small minority have presented an analysis of features extracted from the signals to assess if there is a difference between falls and ADL for those features [e.g. 113,114]. Therefore, the approach of the field as a whole could be characterised as trial and error, where complete systems or classifiers are tested as a single unit and it is not clear how performance can be improved following each test.

Due to the challenges in collecting real-world data, its supply has been limited and going forward this is likely to be the main factor which limits progress on fall detection. Therefore, real-world data is highly valuable and one must ensure the maximum knowledge is gained from the data available. Simply testing a novel system design does not extract a great deal of knowledge from the data, only how well that system performs in comparison to others (although even this is often troublesome, see Chapter 4 for details). Assuming test results are comparable, only the performance change introduced by the sum of all the differences is quantified. Thus, where there is more than one difference between systems, one cannot ascertain which were beneficial, detrimental or had no effect. To test every potential combination of features in turn and compare the performance is unrealistic, testing needs to be highly targeted and this requires a greater knowledge of real-world falls than currently exists.

To identify how performance can be improved, one must examine the components of the system; for fall detection the critical components are the features extracted from the sensor signals and used for classification. If there is not a good distinction between falls and ADL for the features used, then no method of combining them in a classifier will yield good performance. If no features can be found that yield good separation, then the hardware setup used to record the signals must be changed, ideally based on knowledge gained from the prior analysis. It is important to note that providing the features are based on physical characteristics of motion, the results of studies on new features have the potential to provide insights relevant to many fall detection approaches, be they computer vision, thigh-worn or torso-worn accelerometer, or any other approach. In addition, the more knowledge gathered on the characteristics of falls the more likely it is that new, better methods of simulating falls can be developed. For example, if a study using a thigh-worn accelerometer found falls to have multiple impacts, but these were rare for ADL, this would benefit more than just those aiming to detect falls with a thigh-worn accelerometer.

The proposed approach to developing fall detection technology is, conversely, to not focus per se, on building classifiers or fall detection systems. Instead, the focus should be on the study of the characteristics of falls and how they are different from other movements. There is a need to test systems to measure progress in fall detection performance, however, such testing should follow a series of studies of real-world fall and ADL signals to gather evidence which can inform the new design. In addition, following a performance test, it is important to go back and study why false positives and negatives occurred, and to identify where the next stage of development should focus. Thus, it is proposed that the development of fall detection technology should be an iterative process; Figure 3.4 shows a diagram of a proposed iterative development process.

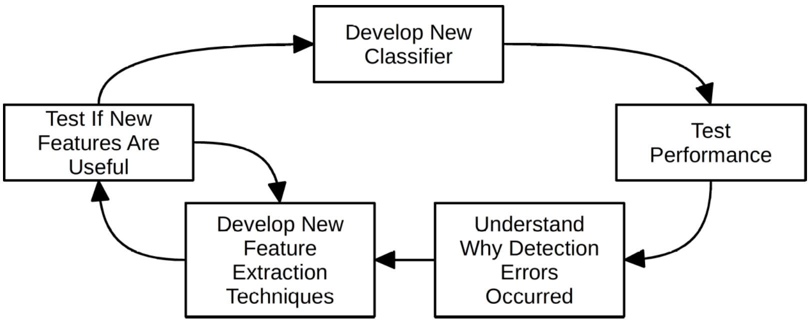


Figure 3.4: Flow diagram of iterative development for fall detection using real-world data.

The critical aspects for improving performance are the feedback from a test of performance through to the development and testing of new features. It is these aspects which have been lacking in the fall detection literature, hence the aim of the research for this thesis was to identify why existing wearable fall detection technology had not achieved acceptable performance and where further development should focus. The identification of these missing elements in the fall detection research, and the recommendation of a new framework for the development of fall detection technology, fulfils the first sub-aim of this research: to formulate a new framework for the development of fall detection technology.

Chapter 4

Methods for the Real-World Evaluation of Fall Detection Technology

Given the previously highlighted issues with simulations of falls (Section 3.4), real-world data is potentially the only source of reliable results for the performance of fall detection technology. Thus, it is crucial to understand the methods used for testing fall detection technology using real-world data so that results can be properly interpreted. The study presented in this chapter aimed to identify how fall detection performance should be quantified, which was the second sub-aim of the research for this thesis. During the time of PhD candidature, the author published a review on the methods for the real-world evaluation of fall detection technology [144], the publication makes up the entirety of this chapter.

4.1 Introduction

Falls in older adults and their related consequences pose a major healthcare challenge that is set to grow over the coming decades [1]. Approximately thirty percent of those over the age of sixty-five experience one or more falls each year, which rises to around forty-five percent in those over eighty [27]. Roughly six percent of older adult falls result in fractured bones [153,154]. Falls are estimated to cost the UK over one billion pounds each year, with fractures being the most costly fall related injury [60].

Even when the injuries are not so serious, fallers often struggle to get up unaided [3,155], sometimes leading to a 'long-lie' where the faller remains trapped on the floor for an extended period of time. Long-lies can lead to dehydration, pressure sores, pneumonia, hypothermia and death [4–6,44]. Further to the physical consequences, the fear of falling can impact on older adults' quality of life. A fear of falling is associated with a decline in physical and mental health, and an increased risk of falling [46]. Estimates suggest that between twenty-five and fifty percent of older adults are fearful of falling and half of these will limit their activities as a result [47,48].

One method used to address the severe consequences associated with falling is the use of a push button alarm system, which can ensure help is received quickly, and reduce the risk of a long-lie. However, studies have shown that eighty percent of fallers do not or cannot activate their alarm following a fall, meaning an alternative approach is needed [3,93]. As a result, there has been extensive research into automatic detection of falls and a broad range of approaches have been developed.

In order to understand the efficacy of the automated fall detection systems, it is important to have a robust method of testing performance. Key to the assessment of these systems is the evaluation of reproducibility and experimental validity [156]. There are two types of experimental validity: internal and external. Internal validity is the extent to which the results truly reflect the capability of the tested system, and were not influenced by other confounding factors or systematic errors. External validity is the extent to which the results can be generalised across people and environments.

External validity has been a central issue in tests of fall detection systems. The poor external validity has been caused by the use of laboratory simulated falls conducted by young healthy adults. The accidental, unexpected and uncontrolled nature of a fall makes it challenging to simulate. When a person simulates a fall the movement is expected, deliberate and carried out in a safe space where injury is highly unlikely. Therefore, reflexes to prevent or lessen the severity of the fall are likely to be suppressed leading to a different pattern of movement. When thirteen previously published approaches were tested using real-world fall data, the performance was found to be considerably worse (mean sensitivity and specificity of 0.57 and 0.83, respectively) than had originally been reported from testing using simulations (mean sensitivity and specificity of 0.91 and 0.99, respectively) [17].

Despite the challenge associated with simulating falls, the vast majority of studies have used simulated fall data (for recent reviews see [8,9]). The use of laboratory simulated falls has been an accepted approach due to the challenge associated with recording real-world falls. The rarity of falls means that recording them is both costly and time consuming. Bagala et al. [17] estimated that to collect 100 falls, 100,000 days of activity would need to be recorded, assuming a fall incidence of one fall per person every three years. Despite this challenge, the focus is now moving to real-world fall data due to the external validity issues inherent in simulated fall based testing. Real-world data, by its very nature provides high ecological validity and therefore contributes to higher external validity.

The use of real-world data, while a significant step forward, does not make the test robust. Other factors such as cohort selection and size are important for external validity. In addition, the use of real-world data does not increase the internal validity, in fact, the level of variation and abundance of confounding factors creates a greater risk of systematic errors. Therefore, careful consideration and planning of both the data collection and test procedure is vital to ensure the validity of results.

All methods of testing fall detection systems share the same basic framework which shapes the whole method from data collection through to data processing. Therefore, a basic understanding of this framework is needed to understand the best method to evaluate fall detector performance. Fall detection is a case of binary classification; each movement is classified as either a fall (positive case) or non-fall (negative case). For each movement there are four possible outcomes:

- True Positive (TP) – Correctly detected fall
- True Negative (TN) – Non-fall movement not detected as a fall
- False Positive (FP) – Classified as a fall when none occurred
- False Negative (FN) – A fall which was not detected

These four values can be represented as a table comparing the actual data with the system's predictions, this is known as a confusion matrix (Figure 4.1). All further measures can be calculated from either a complete confusion matrix or a subset of one. Therefore, studies should aim to collect data and process it in such a way that as many of these four values as possible can be calculated.

		Predicted		
		Fall	Non-Fall	
Actual	Fall	True Positives (TP)	False Negatives (FN)	No. Actual Falls (P)
	Non-Fall	False Positives (FP)	True Negatives (TN)	No. Actual Non-Falls (N)

Figure 4.1: Example confusion matrix.

The aim of this review is to identify the methods which have previously been used to evaluate fall detector performance using real-world data and investigate how the differences in these methods of evaluation effect the results. The review covers the methods of data collection and processing as well as the performance measures which have been used for evaluation. In this review, we aim to identify the strengths and limitations of current approaches and propose a more robust approach of evaluation based on the findings.

4.2 Methods

A systematic search was conducted in August 2017 and repeated in March 2018, using the following on-line literature databases: Medline, Cinahl, Pubmed, Web of Science and IEEE Xplore. The search aimed to find all records where a fall detection technology (hardware or software) had been tested using real-world falls. The search strategy used is shown in Table 4.1. Papers were excluded where no fall detection technology was tested, where tests used fall simulations, or the technology was not aimed at older adults. Only articles available in English were included.

The studies which met the inclusion criteria were assessed with regard to the method used to test the fall detection system. The focus was to assess the robustness of these tests and we therefore did not assess the systems' design or performance. For a comparison of wearable systems see [17] and for a comparison of non-wearable systems see [143]. All included studies tested fall detection technology using real-world fall data. Where studies reported on both tests using simulated data and tests using real-world data, only the methods used for the real-world portion of the data were considered.

Table 4.1: Example Search Strategy for PubMed.

	fall*-detect*[Title/Abstract] OR fall*-sensor*[Title/Abstract] OR fall*-alarm*[Title/abstract]
AND	real-world[Title/Abstract] OR real-life[Title/Abstract] OR free-living[Title/Abstract] OR community-dwelling[Title/Abstract] OR home-dwelling[Title/Abstract] OR domestic-environment[Title/Abstract] OR long-term-care[Title/Abstract] OR care-home[Title/Abstract] OR nursing-home[Title/Abstract] OR hospital[Title/Abstract]

First we reviewed the information studies provided about their participants, how they collected data and the volume of data collected. Next, we examined the methods used to identify fall events and to process the data. Finally, we evaluated the use of each applicable performance measure.

4.3 Results

The systematic search returned 259 unique records. Following application of the selection criteria, twenty-two papers were identified for analysis. The full breakdown of the literature identification process, including the reasons for exclusion, is shown in Figure 4.2. Table 4.2 provides a breakdown of the twenty-two included papers with regard to participant groups, devices used, participant numbers, numbers of recorded falls, the quantity and processing of non-fall data and finally, the performance measures reported. The following sections provide further detail to complement Table 4.2.

4.3.1 Participant Descriptions

The level of detail provided about participants varied considerably. All but three [145–147] of the articles stated whether participants were community dwelling, in long-term care or hospital patients. Five articles did not provide any additional descriptive information on the participants [18,122,142,147,157]. The other eighteen articles describe participant's

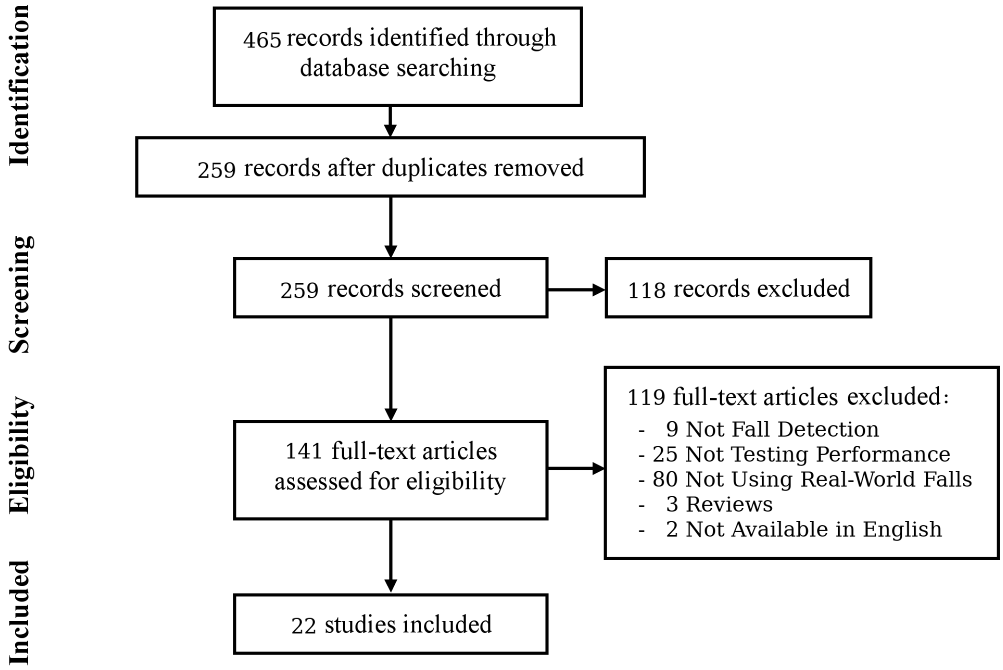


Figure 4.2: Flow diagram of the systematic search.

age, twelve also provide gender information and six provide details of height and weight or BMI [17,19,21,145,158,159]. Four articles provided information on specific medical conditions, three recruited participants with Progressive Supranuclear Palsy [17,109,148] and one included a single older adult with Parkinson's disease [145]. Lipsitz et al. [21] provided the most in-depth description with a breakdown of the proportion of participants with a range of twenty-one comorbidities. Eight articles reported results of mobility assessments [19,20,109,145,146,149,160,161], three articles provided information on walking aid use [143,149,160] and three articles additionally reported results of cognitive assessments [19,20,161]. None of the other fifteen articles reported standardised measures of cognitive or mobility status.

Table 4.2: Summary of papers evaluating fall detection systems using real-world falls.

Author	**Participant Group**	**Additional Information**	**Device Type**	**Number of Participants**	**Number of Falls**	**Quantity of Non-Fall Data and Method of Preparation**	**Performance Measures**
Aziz [109]	Residents of a long-term care facility who had experienced at least one fall in the previous year	Age, mobility assessment	Accelerometer	9	1	214 h Data were divided into 2.5 s time windows with a 1.5 s overlap. The 30 s of data following a fall event were ignored.	**Sensitivity**, Specificity, **FPRT**, TP, FP, FN
	Patients at a hospital geriatrics department with Progressive Supranuclear Palsy	Age	Accelerometer	10	9	178 h	
Bagala [17]	Patients with Progressive Supranuclear Palsy	Age, gender, height, weight	Accelerometer	9	29 the number from each group was not provided	A total of 168 h from seven of the participants. Recordings were divided into 60 s windows and only the 1170 windows where max(RSS) − min(RSS) > 1.01 g were included	**Sensitivity**, **Specificity**, **FPRT**, Precision, NPV, Accuracy
	Community dwelling older adult	None	Accelerometer	1			

Table 4.2: Cont.

Author	Participant Group	Additional Information	Device Type	Number of Participants	Number of Falls	Quantity of Non-Fall Data and Method of Preparation	Performance Measures
Bloch [162]	Patients at a geriatric rehabilitation ward with an identified risk of falling	Age	Working alarm composed of an accelerometer and infrared sensor	10	8	A total of 196 days. Data was processed on-line and the analysis compared the alarm times to reported fall times. Assumed 30 fall like events per day to estimate of the number of non-fall events.	**Sensitivity**, **Specificity**, Precision, NPV, TP
Bourke [122]	Patients at a geriatric rehabilitation unit	None	Accelerometer and gyroscope	42	89	A total of 3466 events extracted using a dynamic detection algorithm and further reduced to 367 events where: max(RSS) > 1.05 g Total length of recorded data was not given.	**Sensitivity**, **Specificity**, Accuracy, ROC AUC

Table 4.2: Cont.

Author	Participant Group	Additional Information	Device Type	Number of Participants	Number of Falls	Quantity of Non-Fall Data and Method of Preparation	Performance Measures
Chaudhuri [18]	Community dwelling older adults	None	Working alarm consisting of an accelerometer, magnetometer, and gyroscope	18	4	A total of 1452.6 days. Details of data preparation not given.	Sensitivity, Specificity, Precision, NPV, Confusion Matrix
Chen [158]	Community dwelling older adults living in geriatric rehabilitation centres	Age, gender, height, weight	Accelerometer	22	22	A total of 22 events. Only data from a 1200 s window around the falls was used, data up to 1 s before each fall were used as non-fall events.	Sensitivity, FPR, Accuracy, Confusion matrix
Debard [150]	Older adults	Age	Camera	4	25	A total of 14,000 h. Only data for the 20 min up to and including the falls were used, this was divided into 2 min windows.	**Sensitivity**, Specificity, **Precision**, Confusion matrix

Table 4.2: Cont.

Author	Participant Group	Additional Information	Device Type	Number of Participants	Number of Falls	Quantity of Non-Fall Data and Method of Preparation	Performance Measures
Debard [149]	Older persons (two community dwelling, one in a nursing home and four in assisted living), two of which did not fall and were excluded	Age, mobility assessment, walking aid use	Camera	7	29	Over 21,000 h recorded. Only data from the 24 h prior to each fall were used which was divided into 1 s windows.	Sensitivity, Precision, PR Curve, PR AUC, TP, FP, FN
Debard [160]	Older persons (two community dwelling, one in a nursing home and four in assisted living), two of which did not fall and were excluded	Age, mobility assessment, walking aid use	Camera	7	29	Over 21,000 h recorded. Only data from the 24 h prior to each fall were used which was divided into 1 s windows.	**Sensitivity**, Precision, PR Curve, **PR AUC**, TP, FP, FN, **FPRT**
Feldwieser [19]	Community dwelling older adults	Age, height, weight, mobility assessments, cognitive assessments	Accelerometer	28	12	A total of 1225.7 days (average daily user wear time 8.1 ± 4.8 h). Details of data preparation not given.	**TP**, FP, FPRT

Table 4.2: Cont.

Author	Participant Group	Additional Information	Device Type	Number of Participants	Number of Falls	Quantity of Non-Fall Data and Method of Preparation	Performance Measures
Gietzelt [161]	Older adults with recurrent falls	Age, gender, mobility assessments, cognitive assessments	Accelerometer and camera	3	4	A total of 10 days. Details of data preparation not given.	TP, FPRT
Godfrey [145]	Older adult with Parkinson's disease	Age, BMI, balance assessment	Accelerometer	1	1	A total of 7 days. No preparatory steps.	TP, FPRT
Hu [159]	Community dwelling older adults with a history of falls	Age, gender, height, weight	Accelerometer and Gyroscope	5	20	A total of 70 days, divided into sliding windows. Window size was varied from 5 to 30 min.	Sensitivity, Specificity
Kangas [20]	Residents of elderly care units	Age, gender, mobility assessments, cognitive assessments	Accelerometer	16	15	A total of 1105 days (average daily user wear time 14.2 ± 6.3 h). Data processed on line, 14 s raw acceleration data where recorded when acceleration of all three axes fell below 0.75 g.	**Sensitivity**, **FPRT**, TP, FP

Table 4.2: Cont.

Author	Participant Group	Additional Information	Device Type	Number of Participants	Number of Falls	Quantity of Non-Fall Data and Method of Preparation	Performance Measures
Lipsitz [21]	Residents of a long-term care facility who had at least once in the previous 12 months	Age, gender, height, weight, BMI, prevalence of 21 comorbidities	Working alarm system using an accelerometer	62	89	A total of 9300 days. Working alarm, raw sensor data not stored, analysis compared the alarm times to reported fall times.	Sensitivity, Precision, TP, FP, FN
Liu [142]	Older adult	None	Doppler radar	1	6	A total of 7 days. No preparatory steps.	TP, FPRT
Palmerini [148]	Patients with Progressive Supranuclear Palsy staying in a geriatric rehabilitation unit	Age, gender	Accelerometer	1	12	A total of 168 h from four of the participants. Recordings were divided into 60 s windows and only the 1170 windows where $\max(RSS) - \min(RSS) >$ 1.01 g were included	Sensitivity, Specificity, FPR, FPRT, Informedness, ROC Curve, **ROC AUC**, FP
	Community dwelling patients with Progressive Supranuclear Palsy	Age, gender	Accelerometer	6	16		
	Community dwelling older adult	Age, gender	Accelerometer	1	1		

Table 4.2: Cont.

Author	Participant Group	Additional Information	Device Type	Number of Participants	Number of Falls	Quantity of Non-Fall Data and Method of Preparation	Performance Measures
Rezaee [157]	Nursing home residents	None	Camera	Not given	48	A total of 163 normal movements extracted from video sequences totalling 57,425 frames. Details of identification not given.	**Sensitivity**, **Accuracy**, **FPR**, Confusion matrix
Skubic [143]	Residents of an older adult independent living facility	Age, gender	Doppler radar	1	13	10 days Details of data preparation not given for any of the datasets.	Sensitivity, FPRT, TP, FP
	Residents of an older adult independent living facility	Age, gender	Kinect	16	9	3,339 days	
	Resident of an older adult independent living facility	Age, gender, mobility device use	Kinect	1	142	601 days	
	Residents of assisted living apartments	Gender	Kinect	67	67	10,707 days	

Table 4.2: Cont.

Author	**Participant Group**	**Additional Information**	**Device Type**	**Number of Participants**	**Number of Falls**	**Quantity of Non-Fall Data and Method of Preparation**	**Performance Measures**
Soaz [146]	Older adult	Age, gender	Accelerometer	1	1	3.5 h No preparatory steps.	Sensitivity, **FPRT**, FP
	Older adults	Age, gender	Accelerometer	14	0	996 h	
Stone [163]	Residents of an older adult independent living facility	Age, gender	Kinect	16	9	A total of 3339 days. Device only stored data for periods where motion was detected.	Sensitivity, FPRT
Yu [147]	FARSEEING data used previously in [17,122] no further details provided	None	Accelerometer	22	22	A total of 2618 normal activities extracted as 1 s windows from the 2 min surrounding the fall signals.	**Sensitivity**, **Precision**, Specificity

Notes: Performance measures reported in the articles abstract are shown in bold. Where a working alarm system was tested this is stated in the Device Type column, otherwise the test was carried out off-line, using the collected dataset. Soaz [146] focused on estimating the false alarm rate, however one real fall was recorded by chance and was included. RSS = Root Sum of Squares; FPRT = False Positive Rate Over Time; NPV = Negative Predictive Value; ROC Curve = Receiver Operating Characteristic Curve; ROC AUC = Area Under ROC Curve; PR Curve = Precision Recall Curve; PR AUC = Area Under Precision Recall Curve; TP = True Positives; FP = False Positives; FN = False Negatives; TN = True Negatives.

4.3.2 Method of Data Collection

All studies used the same general approach of monitoring participants with one or more sensor devices. Studies can be classified into two main categories, those using wearable technology (e.g. accelerometers or gyroscopes) and those using non-wearable technology (e.g. fixed cameras or Kinect sensors). Both approaches have advantages and disadvantages with regard to fall detection. For example, wearable devices are always with the user, however they may forget to wear the device. In contrast, non-wearable devices have a limited capture area but the user can safely forget about them. For a full discussion on the advantages and disadvantages of different sensor types refer to recent reviews [9,14].

Fifteen studies used wearable technology and ten used non-wearable, Table 4.2 shows full details of the devices used in each study. Accelerometers are the most common choice of sensor and have been used in fifteen of the studies [17–21,109,122,145–148,158,159,161,162]. Eight studies tested some form of optical sensor [143,149,150,157,160–163], making them the most common choice of non-wearable devices. One additional study deployed an optical sensor as part of their system, but this did not record any falls so they could not test it [19].

Studies can be further classified based on whether the device used was capable of processing data on-line and raising an alarm when it detected a fall. Three studies deployed functioning wearable alarm systems [18,20,21], one study deployed a system combining wearable and non-wearable devices [162], no studies deployed an alarm system solely using non-wearable devices. Two of the studies which tested working alarm systems did not store the raw sensor data, only recording when the alarm went off [21,162], one article did not state if the raw sensor data was stored [18]. The raw sensor data can be used for future development and testing, and therefore the favoured approach is to store this data.

The availability of the collected data is important for future work and the direct comparison of approaches. None of the studies used publicly available datasets nor made their real-world fall data publicly available. Two studies [147,158] made use of a subset of the FARSEEING repository, which is available on request. The FARSEEING project is a real-world fall repository project funded by the European Union. Four studies [17,109,122,148] were conducted by members of the FARSEEING project or in collaboration with members, and also used data from the FARSEEING repository. No other studies provide any information on the availability of their datasets.

4.3.3 Number of Participants and Falls, and the Volume of Non-Fall Data

There is a large range in the number of participants included, with most studies using small cohorts. One article did not provide any information on the number of participants [157]. Three studies had just a single participant [142,145,146] and one study [143] used data from only one participant in parts of their analysis. The maximum number of participants was sixty-two [21] and the median was nine (IQR four to eighteen).

There was an equally large range in the number of fall events recorded. Two studies included just a single real fall [145,146] and in one of the two datasets used by Aziz et al. [109] only one fall was recorded. The maximum number of falls was eighty-nine, which was achieved in two separate studies [21,122]. The median number of falls contained in the datasets used was 17.5 (IQR 8.25 to 29).

Where reported, the length of the monitoring period varied considerably and comparison is made difficult by the inconsistent choice of reported metrics. Thirteen articles provided the total length of the recorded data, but did not provide details of the proportion where the system was recording participant's movement (participant in the capture area or wearing the device) [18,21,109,142,143,146,149,150,159–163]. The median length of total recorded data, from studies which provided it, was 592 days (IQR 21 to 1,474). Only three articles provided information on device wear time, in these studies, the mean wear times were 8.1 [19], 14.2 [20] and twenty-four [145], hours per day, respectively. None of the articles on non-wearable devices provided information on the proportion of time during which participants were in the capture area.

Six articles did not clearly state the time period over which participants were monitored or the amount of data captured, instead they provided the number of extracted non-fall events [17,122,147,148,157,158]. The number of non-fall events used in these studies ranged from twenty-two [158] to 3,466 [122].

4.3.4 Method of Fall Identification and Validation

One of the main challenges in recording real-world falls is ensuring every fall that occurs is identified accurately. How fall events are identified is influenced by both the choice of device and whether the system is capable of raising alarms in real-time. The device used determines the type and detail of information available for retrospective verification of fall times and types. A camera, for example, provides a greater level of information compared to an accelerometer; assuming the video footage is not highly pre-processed, for privacy reasons, before being stored. Where working alarm systems are deployed, all detected falls can be quickly verified, providing additional robustness over a single reporting method such as staff incident reports.

Four studies [18,20,21,162] deployed a functioning wearable alarm system. As the alarm systems were being validated, a second reporting system was still needed to identify falls which did not trigger an alarm. Three of the studies used staff incident reports in addition to the alarm system [20,21,162]. It was unclear what secondary method of fall identification was used in one of the studies [18]. Of the eighteen studies which analysed the data retrospectively, three identified falls using staff reports [17,109,163], five used participant self-report [19,145,146,159,161] and ten did not state how falls were identified [122,142,143,147–150,157,158,160].

Where self-report of falls is used it is important to consider the cognitive ability of participants, especially their memory. Only two of the five studies which used self-report provide results of assessments of cognitive ability [19,161]. Both of these studies used a Mini Mental State Exam [164]. Feldwieser et al. [19] found no signs of cognitive impairment and Gietzelt et al. [161] found that one of their three participants had cognitive impairment, but does not report how they accounted for this.

It is important to consider that reported fall times might not be accurate and that some falls may not be reported, or may be reported by more than one member of staff with different timestamps. This could, for example, be due to delays in completing the report, delays in the faller being discovered, participant recall problems or staff naturally prioritising helping the faller over checking and reporting the time. Only three articles describe methods to check reported fall times [17,109,159]. Two of these [17,109] used datasets from the FARSEEING repository where expert analysis of the sensor signals in combination with fall reports was used to pinpoint the fall signal. Hu et al. [159] reported correlating self-reported fall times with the signals, but provided no details on how this was carried out.

4.3.5 Methods of Data Processing

There are two approaches for testing real-world fall detection systems, the key difference is how the data is prepared. The first approach is based on simply identifying when falls occur in continuous user movement or a stream of sensor data, we call this the continuous data approach. The second approach is based on a fall detector classifying events as either a fall or not a fall, we call this the event based approach. The following sections explain each of these approaches and review their use. In five studies it was unclear which approach was used [18,19,143,161,163].

4.3.5.1 Continuous Data Approach

The continuous data approach mirrors real-world usage of fall alarm systems where user movement is the input and fall times or alarms are the output. This approach is therefore the primary way of testing deployed fall alarm systems but can also be used for retrospective testing using existing data. The fall detection systems sensors convert movement into a stream of raw data which is then processed by the software component of the system. In this approach all aspects of data processing are part of the fall detection software and are tested as a single unit. To test performance the systems predictions are compared to the actual verified fall times. This comparison allows quantification of the number of true positives (actual and predicted timestamps match), false positives (predicted fall with no actual fall) and false negatives (fall occurred but none was predicted).

True negatives can be quantified if the times when non-falls occurred were recorded, however, non-falls are not defined. In the strictest sense non-falls are everything which is not a fall, but that does not enable their occurrence to be quantified. It is not possible to count when a fall doesn't occur without arbitrarily dividing the time-series data into events, and counting the events where no fall occurred. Such a method of dividing the data would fall under the event based testing approach. In the continuous data approach any segmenting of the data for processing purposes is part of the fall detection system, not the test procedure.

Six studies used the continuous data approach [20,21,142,145,146,162]. Bloch et al. [162] processed the data using the continuous data approach, and then used an assumption of thirty 'fall-like' events per day to calculate a number of true negatives (thirty times number the of days the sensor was in use). The other five studies did not attempt to quantify true negatives.

4.3.5.2 Event Based Approach

The event based approach has its roots in tests using laboratory based simulation datasets. When data is collected in the laboratory a predefined set of movements or events is simulated, the times of these events is known and therefore they can be easily extracted. To test performance all the events must first be labelled as either a fall or not a fall using the record of event times. For each event the label is compared to the software's predictions allowing a complete confusion matrix to be generated.

In real-world data, events are less clearly defined than in simulated data since there is no complete record of the movements which occurred. The creation of events from real-world data has been based on arbitrary rules rather than identification of the underlying movements of the users. The events are labelled using reported fall times, where no fall occurred the event is considered a non-fall. As this method always yields non-fall events, true negatives can be quantified, unlike in the continuous approach.

Eleven studies used the event based approach [17,109,122,147–150,157–160]. The predominant method to create events was based on time windows, where the data is sliced using constant time intervals, for example each sixty seconds of data is one event. However, there is no consensus on what constitutes an event and in practice, a method of reducing the volume of data is often used, for example, to exclude data where no movement was recorded. The time windows can overlap allowing the same data to be processed multiple times, although the rationale for this is not clear.

To create events, one study used 2.5 second windows with a 1.5 second overlap and kept all the events [109]. Two studies divided the data into sixty second windows and used a movement detection algorithm to select events [17,148]. Bourke et al. [122] also used a movement detection algorithm to select events but does not describe the windowing technique. Two studies used the same dataset where the twenty-four hours prior to each fall was divided into one second windows [149,160]. One study used self-reported wear time to reduce the dataset prior to dividing into windows, but does not provide any details about the windowing technique [159].

Three studies used only a limited section of data from around each fall. Debard et al. [150] divided up the twenty minutes of data prior to a fall into two minute windows. Chen et al. [158] only used data from twenty minutes surrounding each fall and used the section of data up to one second prior to impact as non-fall events. Yu et al. [147] divided the two minutes around each fall into one second windows, removed the one second window where the fall occurred and used the remaining windows as non-fall events.

4.3.6 Definition of Performance Measures and Review of Their Use

4.3.6.1 Sensitivity

Sensitivity (also known as recall and true positive rate) is the proportion of falls which are correctly detected (Equation 4.1). The inverse of sensitivity is miss rate (false negative rate) which quantifies the proportion of falls not detected (Equation 4.2). Sensitivity is by far the most commonly reported statistic; it was reported in eighteen of the articles [17,18, 20,21,109,122,143,146–150,157–160,162,163] and could be calculated from the information given in the other four [19,142,145,161].

$$\text{Sensitivity} = \frac{TP}{TP + FN} = \frac{TP}{P} \tag{4.1}$$

$$\text{Miss Rate} = \frac{FN}{FN + TP} = \frac{FN}{P} = 1 - \text{Sensitivity} \tag{4.2}$$

4.3.6.2 Specificity

Specificity (also known as true negative rate) is the proportion of non-fall events which are correctly detected (Equation 4.3). It quantifies the ability to avoid false positives (false alarms). The inverse of specificity is false positive rate, which is the proportion of non-fall events mistakenly detected as falls (Equation 4.4). Nine articles reported specificity [17,18,109,122,147,148,150,159,162] and two reported false positive rate [148,157]. It is unclear whether Chen et al. [158] reported specificity or false positive rate, as the reported number of TN and FP suggest that what they report as specificity is in fact false positive rate. Specificity could be calculated from the information provided in a further two of the studies [149,160].

$$\text{Specificity} = \frac{TN}{TN + FP} = \frac{TN}{N} \tag{4.3}$$

$$\text{False Positive Rate} = \frac{FP}{FP + TN} = \frac{FP}{N} = 1 - \text{Specificity} \tag{4.4}$$

4.3.6.3 False Positive Rate over Time

False Positive Rate over Time (FPRT) has become a popular measure in real-world tests of fall detection. This measure provides information on the frequency of false alarms. Twelve articles report the number of false positives either per hour or per day [17,19,20,109,142, 143,145,146,148,160,161,163] and it could be calculated from the information provided in seven others [18,21,149,150,157–159].

4.3.6.4 Precision

Precision (also known as positive predictive value) is the proportion of alarms which are true falls (Equation 4.5). It therefore provides the probability that an alarm will be an actual fall and not a false alarm. For example, a precision of 0.5 means that half of alarms will be actual falls, and half will be false alarms (one false positive for every detected fall). Eight articles reported precision [17,18,21,147,149,150,160,162] and it could be calculated from the information provided in all of the other articles.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4.5}$$

4.3.6.5 Negative Predictive Value

Negative Predictive Value (NPV) is the proportion of events classified as non-falls which are true non-fall events (Equation 4.6). NPV therefore provides information about the ability to correctly classify non-fall events. NPV will be high if a system correctly ignores many times more non-fall events than the number of falls it fails to detect. Therefore, for false negatives to have any notable effect, the number of falls and non-falls must be approximately equal. However, in real-world fall data falls are usually much less frequent than non-fall events, which limits the insights yielded from NPV as systems typically score over 0.99 out of one [17,18,162]. Three articles reported NPV in their results [17,18,162]. NPV could also be calculated from the information provided in eleven of the other articles [21,109,122,147–150,157–160].

$$\text{Negative Predictive Value} = \frac{TN}{TN + FN} \tag{4.6}$$

4.3.6.6 Accuracy

Accuracy is the proportion of predictions which were correct (Equation 4.7). Accuracy is a measure which summarises the whole confusion matrix in a single value. Accuracy's major limitation is the inability to handle imbalanced datasets, for example, in real-world fall data where there are many more non-fall events than falls. Similar to NPV, accuracy is dominated by the larger group and the effect is proportional to the size of the imbalance. Therefore, in real-world fall detection studies, accuracy is skewed towards the correct detection of non-fall events over the correct detection of falls. For example, in eight of the algorithms tested by Bagala et al. [17] the accuracies were greater than 0.9 with sensitivities below 0.6, in one case an accuracy of 0.96 with a sensitivity of 0.14. Four articles reported accuracy [17,122,157,158] and it could be calculated from the results provided in seven of the other articles [18,109,147–150,160].

$$\text{Accuracy} = \frac{TP + TN}{P + N} \tag{4.7}$$

4.3.6.7 F-Measure

F-measure (also known as F-score) is the harmonic mean of sensitivity and precision (Equation 4.8). F-measure, therefore, considers all outcomes except true negatives (non-falls). In fall detection, the priorities are detected falls (TP), missed falls (FN) and false alarms (FP). F-measure considers all of these outcomes and therefore provides a good overview of performance. No articles report a value for F-measure, however it could be easily calculated from their results as eight articles [17,18,21,147,149,150,160,162] reported both sensitivity and precision and all but two [159,163] reported enough information to calculate both sensitivity and precision.

$$\text{F-measure} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \tag{4.8}$$

4.3.6.8 Informedness

Informedness (also known as Youden's J Statistics or Youden's Index) is a statistic which combines sensitivity and specificity (Equation 4.9). It is the probability that predictions are informed versus a pure guess. Informedness is linked to the proportion of cases classified correctly. However, unlike accuracy, it is robust to an imbalance in the number of fall and non-fall events. This is achieved through equal weighting of sensitivity and specificity which are in turn the proportions of falls detected and non-falls correctly ignored. The value ranges from negative one to positive one. Zero indicates predictions are no better than guessing, positive one indicates perfect predictions and negative one indicates all predictions are the opposite of the true value. In cases where the value is negative, the output classes can simply be swapped over. One study reported informedness [148], however, twelve other articles reported both sensitivity and specificity or false positive rate, or the information necessary to calculate them [17,18,109,122,147,149,150,157,158,160,162], so informedness could be calculated from their results.

$$\text{Informedness} = \text{Sensitivity} + \text{Specificity} - 1 \tag{4.9}$$

4.3.6.9 Markedness

Markedness is a statistic which combines precision and NPV (Equation 4.10). Markedness is linked with the proportion of predictions which are correct. It combines the proportion of correct positive and negative predictions with equal weighting and is therefore unaffected by imbalance in the number of positive and negative predictions. As with informedness, the result is a value between negative and positive one. No articles reported markedness, but twelve did report enough information for markedness to be calculated [17,18,109,122,147–150,157,158,160,162].

$$\text{Markedness} = \text{Precision} + \text{NPV} - 1 \tag{4.10}$$

4.3.6.10 Matthews Correlation Coefficient

Matthews Correlation Coefficient (MCC) is the geometric mean of informedness and markedness (Equations 4.11, 4.12). It should be noted that Equation 4.11 only works if informedness and markedness are both positive, Equation 4.12 works in all cases. MCC considers both the proportion of events classified correctly and the proportion of correct predictions and is therefore robust to imbalanced datasets. The result is a value between negative and positive one as with both informedness and markedness. None of the articles reported MCC, enough information to calculate MCC was given in fourteen articles [17,18,21,109,122,147–150,157–160,162].

$$\text{MCC} = \sqrt{\text{Informedness} \times \text{Markedness}} \tag{4.11}$$

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{4.12}$$

4.3.6.11 Receiver Operating Characteristic Curve

A Receiver Operating Characteristic (ROC) Curve is a plot of sensitivity versus false positive rate as the primary threshold of the classifier is adjusted. ROC curves can therefore be used to understand the trade-off between sensitivity and false positive rate and optimise a primary threshold. There could be debate as to which balance of sensitivity and false positives is optimal, therefore a ROC curve provides useful insight. However, it is difficult to compare systems robustly based on a curve. Consequently, it is in the optimisation where ROC curves are best used, rather than final results, as only the optimised version will be deployed.

ROC curves can be reduced to a single number by calculating the area under the curve (AUC). AUC has been found to be a poor measure for comparing classifiers, particularly where the sample size is small [165–167]. Two studies have used ROC analysis and reported AUC [122,148].

4.3.6.12 Precision-Recall Curve

A precision-recall (PR) curve is similar to a ROC curve, the difference is that precision is used instead of false positive rate and the term recall is used in place of sensitivity. PR curves are preferred over ROC curves when there is a large imbalance in the data [168]. Calculating AUC for PR curves is more challenging than for ROC curves as precision does not increase linearly, meaning linear interpolation yields incorrect results [168]. Two studies reported PR AUC [149,160], although it is unclear how PR AUC was calculated in these studies.

4.4 Discussion

This is the first review to be conducted on the methods used to evaluate real-world performance of fall detection systems. Ensuring a sound method is critical for meaningful results, therefore reflecting on the way studies are conducted and seeking improvements to the method is vital in emerging areas of research where no consensus has yet been reached. The real-world testing of fall detection systems is currently in its infancy and this is reflected in our findings. The method is highly variable across studies, which makes comparing the results difficult if not impossible. The following three sections discuss the key issues and make recommendations for future studies.

4.4.1 Data Collection and Preparation

One major aspect which leads to variation between studies is the participant groups and the differences in the movements and behaviours captured by the sensor systems. If insufficient detail is gathered about participants it is challenging to reproduce the findings as differing results could be due to differing participant characteristics. In addition, one may want to collect new data comparable to that used in a previous study for the purpose of comparing the performance of a new system using different sensors with previously tested systems. Information gathered about participants was both inconsistent and insufficient to allow the data collection to be reproduced.

A comprehensive consensus process has previously been carried out by the FARSEEING consortium [169]. As part of the consensus process the group identified a minimum set of clinical measures which they deemed essential for the interpretation of real-world fall data. The measures included age, height, weight, gender, fall history, assistive device use as well as assessments of mobility, cognitive impairments and visual impairments. None of the reported studies have implemented these recommendations.

Cognitive and mobility tests provide useful information about fall risk and the likelihood of false positives caused by events such as 'falling into a chair' or improper use of the device. Compared to standard metrics such as age, height and weight, assessments of mobility and cognition provide a much deeper insight into participant's fall risk and movement characteristics. Therefore, standardised cognitive and mobility assessments should be prioritised. Deeper insights into participant's movements could be achieved though continuous profiling using activity monitoring software to process the recorded dataset. However, development and validation of activity monitoring software may be a barrier unless an existing activity monitoring system is used for the data collection. Where such profiling is possible details should be reported to enhance the interpretation of results.

Another critical aspect of the test is the size of the dataset. Currently, the datasets used are generally small, have been collected with a low number of participants and contain only a few falls. Small datasets reduce the validity of the test and hinder reproducibility. Where the dataset is small either due to few participants, a low incidence of falls or both, it is possible that only a limited subset of movements and fall types were captured. In such cases comparisons of results to tests of other systems is difficult as the dataset may be the main cause of differences in reported performance. Further, the generalisability of results is questionable where the sample size is small. The small datasets are one factor which makes it difficult to understand which systems perform the best and therefore where future development should focus. The other main factors are the different populations recruited for studies and the limited insights into how this affects the fundamental aspect of the data, the movements captured.

Due to the known challenges in recording fall signals, the only feasible way for most researchers to gain access to a large number of fall signals is through collaboration. In addition, if systems are tested using the same data, the results are directly comparable. Therefore, large shared test datasets are needed to allow the performance of fall detection software to be compared. To facilitate the sharing of datasets, the FARSEEING consortium have established a data repository which currently contains over 300 fall signals [170]. However, more studies are needed to generate datasets that can be added to the repository and used for robust testing of devices and development of improved software.

Even with shared data, there is still an issue of how to ensure all fall signals are accurately identified. We have identified that the method used to identify the fall signals is poorly described in published studies, leaving a large gap in our understanding of how the dataset was prepared. The current prevailing method to identify fall signals is expert signal analysis to verify participant or staff reported fall times. There is a risk that not all falls are reported, leading to real falls being included as non-fall data. Expert signal analysis cannot overcome the issue of under reporting, but does at least give greater confidence that inaccurate reported times were corrected and all included fall signals were real falls.

Expert signal analysis, while clearly better than no verification, could lead to bias. Currently there is an insufficient understanding of fall signals due to a limited number of recorded falls and a lack of research into the profile of the signals. Our limited understanding could lead to atypical falls not being verified and thus excluded. There is a risk that systems are designed to detect certain signal profiles as falls and only these profiles are being verified as falls. Therefore the results could be artificially improved through restricting the test data.

Unless a gold standard fall reporting system is used, such as video analysis, studies will be limited in their ability to verify fall signals, under reporting of falls will remain a concern and there is a risk of bias in the verification process needed to compensate for the inaccuracies of the 'silver standard' reporting system. The current lack of standardised method or gold standard, and the lack of reporting how fall signals were identified and verified, inhibits understanding of results. A consensus is needed on the process for fall signal identification and studies should clearly report their methods.

4.4.2 Data Processing

Two approaches were identified for preparing sensor signals for fall detection system testing and we named these the continuous data approach and the event based approach. Both approaches have issues surrounding what constitutes a non-fall. In the continuous data approach the issue is centred around the definition and identification of non-falls. In the event based approach non-fall events can be defined as any event which is not a fall.

However, events could be defined as anything which is either a fall event or non-fall event, and since falls are defined, the issue returns to what constitutes a non-fall.

The strictest definition of non-falls as everything which is not a fall is not particularly useful. This definition does not allow non-falls to be quantified in the continuous data approach and provides no indication of how the data should be divided into events for the event based approach. A more helpful concept is that of fall-like movements, a subset of non-falls which share characteristics with falls. The FARSEEING consortium defined a fall as “an unexpected event in which the person comes to rest on the ground, floor or lower level” [26]. A fall-like movement could therefore, by removing the unexpected clause, be defined as “any event in which the person comes to rest on the ground, floor or lower level”.

With a definition for fall-like events these could be recorded, at least theoretically, in the same manner as falls and therefore, allow true negatives to be quantified robustly. In reality it is not feasible for a researcher to record the times of all fall-like movements in the same way that falls are recorded, due to the vast quantity which would occur. An automated system would be more practical, although it is unlikely to be easier to develop automated fall-like detection than automated fall detection systems. Consequently, researchers must consider if the development of fall-like movement detection systems is worth the investment, simply to extend the testing of fall-detection systems. Given that a robust evaluation of fall detection systems can be achieved without the need for true negatives, and hence non-fall or fall-like movements, we suggest that automated fall-like movement detection is unlikely to bring benefits which outweigh the required investment.

4.4.3 Performance Measures

It is challenging to compare results across studies or determine the current state-of-the-art due to disparity in the choice of measures reported and challenges calculating unreported measures. The measures used to report and interpret performance vary widely across studies and not all studies report the basic results from which all measures can be calculated (TP, FP, FN and TN). Where TP, FP, FN and TN are not reported these can only be estimated, due to rounding of the reported results. Using one of the tests reported by Bourke et al. [122] as an example, the number of FP could be any value between eighteen and fifty-one based on the reported specificity of 0.99 with 3,466 total non-falls. To facilitate the calculation of additional measures, future studies should report TP, FP, FN and TN if these can be calculated robustly and are used in the calculation of the reported performance measures.

In addition to reporting enough information to allow further measures to be calculated, it is important that the headline measures give a true reflection of performance and allow robust comparisons to be made with other systems. Sensitivity has been a mainstay in previous studies, it is an important aspect of system performance. Sensitivity only quantifies the ability to detect falls, it does not consider false positives. The question is therefore which measure to pair sensitivity with to provide understanding of the ability to avoid false positives. In addition, a single combined measure which considers both aspects is important in order to understand the overall level of performance.

Specificity has been the most common choice of measure to quantify the ability to avoid false alarms in laboratory based testing [9] and it has remained a common choice in real-world tests. Specificity considers how well non-fall events are classified, it could therefore be considered sensitivity's natural counterpart. The weakness of specificity in the context of real-world fall detection is the reliance on non-falls, which are poorly defined and troublesome to identify.

The need for researchers to design or select methods for non-fall identification opens up a considerable possibility of bias. A method could be used which suits the specific system and dataset causing distortion of the results and hindering comparisons with other systems. In the case of specificity, the difficulty of the test is very much determined by the definition of a non-fall; the more inclusive the definition, the more non-fall events and therefore the higher the score for the same number of false positives. This effect can be seen in the study of Bourke et al. [122], where tests were conducted twice using different definitions of non-falls. With the most restrictive definition of non-falls, specificity ranged from 0.83 to 0.91. With the more open definition, specificity was consistently 0.98 or greater. Expanding the definition includes more movements which are less fall-like, thus it creates an easier test.

It is hard to prevent bias in selecting a definition of non-falls as it is likely unintentional. One solution is to remove the need to select a method on a study by study basis, however, standardising the method is challenging. Since there is currently no clear way to standardise non-fall identification, the best option may simply be to avoid them altogether. A solution might be standard publicly available datasets, with an agreed method to identify non-fall events. In such a case, the results are comparable to each other, but not to other studies using other datasets or methods.

Using standard data is challenging due to the vast array of sensors which could be used and the huge number of combinations. It is simply not possible to have a single dataset used to test all systems. Furthermore, it seems impossible to identify all types of relevant non-fall movements needed for a universal standard dataset. Any measures which rely on non-falls (specificity, NPV, accuracy, informedness, markedness, MCC and ROC AUC) are subject to the above problems and therefore should not be used as a primary measure. Where measures reliant on non-falls are used the methods should be described in detail and their limitations should be made clear to avoid confusion and misinterpretation.

The issues surrounding non-falls substantially reduces the options for quantifying the ability to avoid false positives and gauge overall performance. There are four possible measures which do not rely on non-falls, these are FPRT, precision, F-measure and PR AUC.

FPRT is a useful measure to understand the frequency of false alarms, however differences in the datasets affect the calculation. Wear time or time in the capture area must be considered, as false positives will, most likely, be far lower when the device is not in use. Another consideration is which hours of the day the device is in use; false positive rate during night time hours would be very different to day time hours. Reporting of times when the device was monitoring participants was found to be inadequate. Of the eleven articles which reported FPRT only two clearly reported wear time or time in the capture area [19,20] and none reported any details on the distribution of this time throughout the day.

Our findings suggest that there is a lack of an agreed and clearly defined method to calculate FPRT. Only one study clearly states that FPRT was calculated using solely the time a participant was being monitored by the device [20]. None of the other studies appear to have taken usage time into account when calculating FPRT. If usage time is not considered or reported it is unclear what extent device usage, or lack thereof affected the result. An unused system is unlikely to produce false positives. The issues in identifying wear time or time in the capture area could make FPRT an unreliable measure to compare across studies. Although users and clinicians may find the rate of false positives over time useful, it might be better to use a rate of something other than time.

Precision is an alternative to specificity and FPRT, it quantifies the false positives (FP) in relation to detected falls (TP). TP and FP should, for any reasonable level of performance, be in the same order of magnitude, therefore precision is resilient to the imbalance in the data. Further, the ratio between TP and FP is unlikely to be notably affected by usage time, if a device is used half of the time, TP and FP would be expected to be half compared to full device usage. Therefore, compared to FPRT, precision is far less affected by device usage, or lack thereof. The proportion of fall predictions which were true falls could be more useful than FPRT since frequent false positives may be acceptable to a frequent faller, assuming the falls are detected. Precision should be the primary measure of the ability to avoid false positives.

Sensitivity and precision together quantify the ability to detect falls and avoid false alarms, therefore providing a complete portrayal of performance. In addition to sensitivity and precision it is important to have a single measure which can quantify the trade-off between them. PR AUC is one possible option, however it considers the performance of multiple sub-optimum versions of the system as the system's parameters are adjusted. Since only the optimised system can be deployed, it is the optimised version which should be the focal point of the evaluation. F-measure, the harmonic mean of sensitivity and precision, appears to be the most suitable single measure for objective comparison. This trio of measures has two major advantages in robustness: (1) it does not rely on non-falls and (2) it is resistant to issues surrounding wear time and time in the capture area. Future studies should report sensitivity, precision and F-measure, and F-measure should be used as the standard for comparing systems.

4.5 Summary and Conclusions

As focus in fall detection performance evaluation shifts from simulated to real-world fall data, one must consider if the approach used for evaluating on simulations is optimum for real-world data. Through examining the published articles on evaluation of real-world fall detection, two issues have become apparent:

1. The approaches to quantifying performance are inconsistent and many studies use measures which provide limited representation of performance.
2. The number of falls is generally small and study populations are diverse, making comparison between the datasets and results difficult.

It is critical that a consensus is reached on the most appropriate method to evaluate real-world performance of fall detection systems.

To address the issues with the datasets there needs to be greater collaboration and sharing of data. The FARSEEING consortium have made substantial steps to facilitate data sharing and have recorded over 300 falls through collaboration between six institutions [170]. Six of the twenty-two studies published to date have used parts of this data to develop or test approaches to fall detection [17,109,122,147,148,158], highlighting the importance of this data. However, further work is still needed to grow the volume of available data, record more falls, improve standardisation and further develop fall detection technology. Only through collaboration will the collection of a dataset large enough for robust development and testing become possible.

To address the issues surrounding how performance is quantified studies should avoid the need for non-falls. The concept is poorly defined and standardisation seems to be extremely problematic. The concept of non-falls is only needed to allow the calculation of measures such as specificity and accuracy, both of which are common in simulation based studies [9]. However, quantification of the difference in false alarm rate between simulated and real-world tests is not possible due to the disparity of the data. Therefore, traditional measures such as specificity and accuracy are of little value. Continued use of these traditional measures may lead to confusion and improper interpretation of performance. Measures which do not depend on non-falls should be used instead of these traditional measures. Sensitivity and precision should be the cornerstones of the evaluation with F-measure used for the objective comparison of systems.

Chapter 5

Pilot Study

5.1 Introduction

Previous approaches to automatic fall detection have not performed well in real-world tests and the reports on their design and evaluation provide insufficient insights into how to improve them (Sections 3.6, 3.7). There is a need for research into how falls differ from other movements, however, this requires a real-world dataset which captures both ADL and falls (Section 3.7); this is challenging and time-consuming to collect (Section 3.3). Given the investment required to collect real-world fall data, the methods of collection and processing needed to be first tested under controlled conditions to reduce the chance of issues occurring and to maximise the quality of the collected data. For this reason, a pilot study was conducted in which data were collected using simulated falls to test the data collection and planned analysis processes. Simulated falls were deemed appropriate to test that the methods of recording falls were suitable and to test data handling and signal processing software as the first step towards a study of real-world falls monitoring.

5.1.1 Choice of Sensor

The choice of sensor was the most important aspect of the study design and was crucial in shaping the study protocol. The primary aim of this study was to prepare for further research into which features of real-falls best distinguish them from other movements.

Therefore, the choice of sensor was heavily influenced by the practicalities of real-world data collection. This section explains the decisions made on whether to use wearable or non-wearable devices, which sensors to use, how many devices to use and where to place devices.

Video cameras provide possibly the richest set of data as they can capture the movement of the entire body in a high level of detail. However, as discussed earlier, in real-world contexts the privacy concerns could result in a lack of coverage in private areas and a high risk of missed falls. In addition, with video cameras, or indeed any non-wearable sensor, there are ethical concerns surrounding the collection of data on those who have not provided consent to participate. Since non-wearable devices monitor a space rather than an individual it is not possible to avoid capturing data on non-participants. The inability to selectively capture data may present a problem for data collection in care facilities, where there are many communal areas. Finally, the use of non-wearable devices for the recording of real falls requires a system to be retrofitted into the buildings where participants reside. This need to retrofit systems not only incurs substantial cost but may also be a barrier to collaboration with third-parties who are vital for participant access.

Wearable devices only monitor the wearer and hence avoid the issues raised above. The relatively simple setup associated with wearable devices reduces the investment in each site compared to the use of non-wearable devices. Thus, wearable devices facilitate the inclusion of sites with a lower number of potential participants and could allow for a wider pool from which to recruit participants. The simple setup afforded by wearable devices provides much greater freedom in collaboration with third parties for access to participants and could aid in the collection of a suitably large dataset. The disadvantages of wearable devices are their limited battery life and the need for the user to remember to wear the device (or for someone to ensure they are), however, these can be minimised by careful device selection.

With the current technology, the advantages of wearable devices outweigh their disadvantages and they appear to be the most suitable method to study real-world falls. Of the sensors previously used in wearable devices for fall detection research, accelerometers appeared to be the most promising. Accelerometers have formed the basis of nearly all the fall detection systems proposed in the literature; other sensors have most commonly been used to provide supplementary data (Section 3.5.2). Accelerometers can be used for the detection of impact, to infer posture, estimate vertical motion and estimate velocity

(Section 3.5.2.1). The combination of gyroscopes and magnetometers with accelerometers facilitates a more accurate estimation of orientation and therefore estimation of vertical acceleration and velocity. However, each additional sensor adds to the power consumption which either reduces battery life or requires a larger device to house a larger battery, neither of which is desirable.

To record a relatively large set of real falls comparable in size to the largest datasets used in published studies (approximately 100, see Chapter 4), it is estimated that between 10,000 and 100,000 days of recording would be needed [17,19–21]. Therefore, a balance must be struck between participant numbers and the length of the monitoring period for each participant. Based on the estimated occurrence of falls, to record 100 falls with 100 participants, each participant would need to be monitored for between ten and 100 days. If participants are to wear a monitoring device for close to twenty-four hours per day over a relatively long period, it must be comfortable to wear and unobtrusive. Consequentially, a small and lightweight device is preferable to large or heavy one and long battery life is important to minimise inconvenience associated with swapping devices or recharging.

Wearable devices attached to multiple body segments provide greater insight into the movement and posture of the body than a single device. However, each additional device adds inconvenience to participants and thus may both hinder participant recruitment and lead to higher withdrawal rates. Each additional device also adds complexity to the study as one must keep track of which device was worn on each part of the body. If participants inadvertently mix up the devices or there is any confusion over which body part a device was worn on, the data will not be usable. There are clear drawbacks in the use of multiple wearable devices which must be weighed against the benefits. Given research recording real-falls is in its infancy, the simplicity of a single device is preferable.

If only a single device is to be used, then the placement of that device is critical. In previous research a lumbar placement has been common; due to proximity to the centre of mass, it is a good location for estimation of whole-body motion [8,9]. The ability to estimate posture post-fall could be a useful feature in fall detection, however, a lumbar-worn accelerometer cannot be used to robustly distinguish sitting from standing as the torso angle is similar, it can only distinguish lying postures from standing and sitting. A fall may not necessarily result in a lying posture; if a fall occurs near furniture or a wall, the faller may come to rest in a seated posture with the furniture or wall providing support. Therefore, the ability to distinguish sitting from standing could be important for fall research.

The torso and thigh are the best locations for identification of the three major postures (standing, sitting and lying), although distinguishing all three robustly from either location is problematic. Other locations, such as the wrist, may provide benefit in terms of ease of wear and comfort but do not provide such usable posture information. A thigh-worn accelerometer can robustly distinguish standing and sitting using the angle of the thigh with respect to gravity, however, distinguishing sitting from lying is challenging. An algorithm has been developed to detect long periods of lying based on the rotation of the thigh about the longitudinal axis of the body; the reported sensitivity and specificity were 0.97 and 0.93 respectively [171].

The algorithm developed by Lyden et al. [171] was designed primarily to detect periods of lying in bed, where rolling onto the side is common. It worked based on classification of possible sitting or lying (sedentary) periods as lying if rotation of the thigh occurred, otherwise the whole period was classified as sitting. A pair of thresholds at ± 0.9 g on the device's Y-axis (which when worn aligns with the transverse axis of the body) were used to detect lying. Therefore, the algorithm would only classify a sedentary period as lying if the wearer rolled onto their side during the period where they were sedentary. The approach proposed by Lyden et al. [171] may not be suitable for research on falls, where a period of lying may only be short and sufficient rotation of the thigh to cross the thresholds they derived may not occur. However, their algorithm does provide a strong foundation for further development.

In light of the recent work on a method to distinguish sitting and lying [171], the placement of an accelerometer on the thigh appears to provide the most detailed postural information. The thigh is also relatively close to the centre of mass and so is suitable for estimation of whole-body motion. Therefore, for research into falls, the thigh is the optimal location for the placement of a single accelerometer device.

The use of an existing tried and tested device is important to ensure robust and reliable collection of data, especially for twenty-four seven monitoring. The activPAL3™ device (PAL Technologies, Glasgow, Scotland) contains a triaxial accelerometer and is designed to be worn on the midline of the anterior aspect of the thigh. The marketed purpose of the activPAL device is activity tracking in research, it has been widely used and there are over 2,500 published articles which feature activPAL [172]. In addition to providing activity data, the raw accelerometer signals can be retrieved from the device for custom analysis.

The raw data is sampled at twenty hertz with a range of plus or minus two times earth's gravity ($\pm 19.62\ ms^{-2}$).

PAL Technologies produce two variants of the activPAL3, the original activPAL3 devices measure fifty-two by thirty-five by seven millimetres and weigh twenty grams, the later activPAL3 micro devices provide the same features in a smaller package which measures forty-three by twenty-three by five millimetres and weighs ten grams. The activPAL device is capable of up to fourteen days of continuous recording on a single charge, making it suitable for long-term monitoring. It has been used in many studies of older adults which between them have included thousands of participants [173,174]. Typically, activPAL devices have been used for continuous monitoring over seven day periods [173,174], however continuous use over fourteen days has been reported in the literature [175]. The activPAL3 device is small, lightweight, provides relatively long recording periods and has been used successfully in many studies with older adults; it therefore met the requirements and was selected for use in this research.

5.1.2 Study Design

The study aimed to pilot test the use of a thigh-worn activPAL3 accelerometer for the collection of a dataset on activities of daily living and falls, with a view to research features capable of reliably distinguishing fall events from the other data. Based on previous research it was reasonable to assume that a fall detection system might need to be able to capture data associated with vertical motion, impact, and posture change (Section 3.6.1), all of which have been used in previous work [e.g. 20,106]. Methods to measure impact and vertical motion with a body-worn accelerometer have been commonly used in previous fall detection studies (Section 3.5.2.1); these methods could be used with the activPAL3 device. By contrast, research on the use of a thigh-worn accelerometer to capture posture before, during and after falls is limited; to the author's knowledge, no studies have been published. Therefore, this study aimed to develop and test algorithms for the classification of posture, using a thigh-worn accelerometer, before and after a fall.

A proprietary algorithm is provided by the manufacturer to allow the activPAL3 device to classify upright and sedentary (sitting or lying) postures. However, due to being proprietary, the workings of this algorithm are unknown and it is difficult to integrate into custom analysis software. There is a need to develop an open algorithm to carry out the upright and sedentary classification so that it can be tailored to the needs of this research. Lyden et al. [171] developed an algorithm to further classify sedentary periods into sitting or lying, however, further development was needed to ensure post-fall lying periods could be detected. Thus, as part of this study, triaxial accelerometer signals were recorded during standing, sitting and lying postures to develop, optimise and test posture classification techniques. In addition, triaxial accelerometer signals were recorded during simulated falls to provide test data separate from that used to build the algorithms, so that their performance in detecting pre and post-fall posture could be validated. The second purpose was to assess the occurrence of signal clipping during a fall and thus the suitability of the activPAL3 device's ± 2 g range for recording fall signals.

5.2 Lab Simulations of Postures and Falls

5.2.1 Participant Recruitment

The study protocol was approved by the University of Salford research ethics committee (reference HSCR14/72, see appendix B). Participants were recruited via emails sent to university staff and students (see appendix C.1). Written information detailing the study (see appendix C.2) was given to participants at least twenty-four hours before taking part in the study. Upon arriving at the laboratory, participants were prompted to ask any remaining questions they may have, before providing written consent including a confirmation that none of the exclusion criteria applied to them (see appendix C.3). Participants were excluded from the study if they were:

- Taking medication that might affect their ability to participate
- Advised to only do physical activity recommended by a doctor
- Receiving treatment from a doctor or other medical professional (e.g. physiotherapist)
- Suffering from any of the following (or similar): diabetes, epilepsy, seizures, osteoporosis, arthritis, any cardiovascular or respiratory disorder
- Recently suffered a bone fracture (within the previous twenty-four months)
- Currently suffering from any musculoskeletal injuries
- Previously suffered a concussion or other head injury
- Potentially pregnant or had recently given birth (within three months)
- Currently feeling unwell

5.2.2 Protocol

Participants attended the laboratory on a single occasion. Data were collected using an activPAL3C™ device (PAL Technologies Ltd, Glasgow, Scotland), a small triaxial accelerometer-based activity monitor. The device was attached directly to the skin on the midline of the anterior aspect of the right thigh (see Figure 5.1) using a PALsticky (double-sided hydrogel adhesive pad). The triaxial accelerometer data were downloaded from the activPAL device and stored for later analysis.

Figure 5.1: Placement of the activPAL3C device on the thigh.

Participants were guided through the protocol using a custom-written JavaScript application projected onto a screen in the laboratory. The application was developed as a cross-platform application, which could run in any modern web browser, allowing reliable performance on multiple devices in the lab with minimal setup. Four main functions were built into the design: (1) to provide a standard set of instructions to participants, (2) to control the time spent in and between each activity, (3) to record the start and end time of each activity and (4) to display a clock used to synchronise video footage with the accelerometer data. The behaviour of the application was similar to a slide show, but with added capabilities.

A diagrammatic overview of the protocol is shown in Figure 5.2. In brief, participants performed eighteen on-the-floor postures, nine activities of daily living (Section 5.2.3) and eighteen simulated falls (Section 5.2.4). Before each activity participants were shown an instruction slide (details of these are provided in sections Section 5.2.3 and Section 5.2.4).

Participants stood for a minimum of fifteen seconds to read the instructions, this ensured there was a clear separation between each activity in the accelerometer data. Once participants were standing in the matted area, the experimenter advanced the slide to the instructions for the next activity which started a fifteen-second timer; a red square was displayed below the instructions during the fifteen seconds, after fifteen seconds passed the square turned green. When the participant started the activity, the experimenter advanced the slide, which triggered the time to be recorded and a fifteen-second on-screen countdown to begin. When the fifteen seconds ended a beep sounded and participants were asked to stand up in their own time. As the participant transitioned to a standing posture, the experimenter advanced the slide to show the next instruction which simultaneously triggered the time to be recorded and a fifteen-second timer to start.

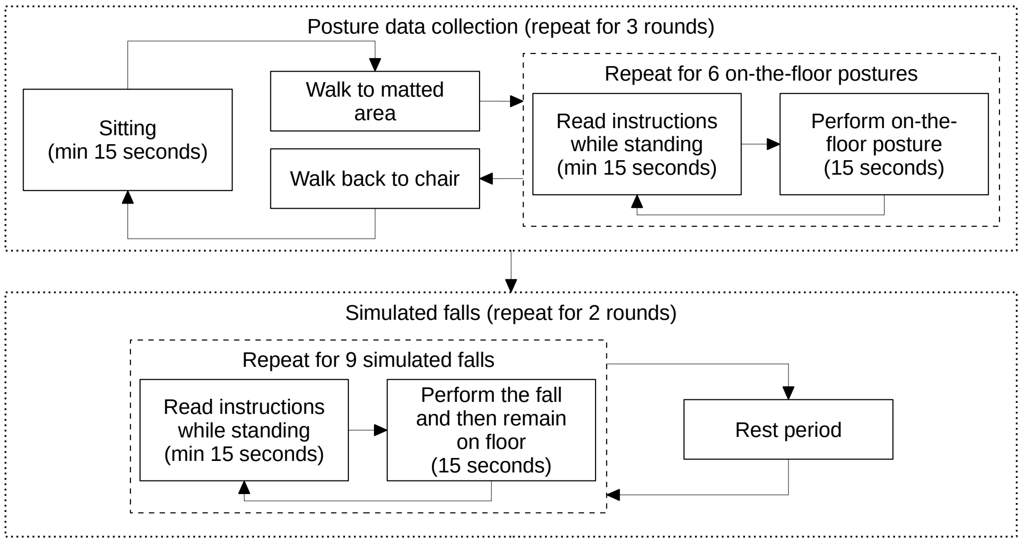


Figure 5.2: Overview of the pilot study protocol.

The protocol was filmed using a single tripod-mounted camera using standard definition (640×480 pixels) at thirty frames per second. The video footage was transferred to an encrypted drive and stored for later analysis. The clock projected as part of the JavaScript application was in view of the camera throughout the protocol and was used to verify the start and end time of each activity. The video footage was used for the analysis of each simulated fall in conjunction with the accelerometer data to provide a greater understanding of the signals.

The protocol was carried out on a matted area to ensure the safety of participants. The majority of previous studies have simulated falls onto crash mats [e.g. 102,106,107,115,119]. Crash mats deform upon impact providing a cushioned landing, however, in doing so the landing posture is altered. Since posture analysis formed a key part of this study a new approach was developed.

A preliminary trial was conducted to find an alternative type of mat, firm enough not to dramatically affect posture but with sufficient impact absorption to protect participants.

Three members of the research team trialled simulated falls onto different types of gymnastics and aerobics mats in a variety of layered arrangements. The best combination was a stack consisting of a thirty-two-millimetre thick gymnastics mat with three fifteen millimetre thick aerobics mats layered on top. These mats provided a soft landing surface without dramatically affecting the landing posture. A matted area 2.5 metres wide and four metres long was constructed in the centre of the laboratory, with a two-metre area around the mats free from furniture and other equipment.

5.2.3 On-the-floor Postures and ADL

Participants were guided through the set of activities shown in Table 5.1 using the JavaScript application. The majority of these activities are self-explanatory and no further information was given beyond the name shown in Table 5.1. For "Lying on Back (Thigh Inverted)" participants were asked to lie on their back and bring their feet towards them so their knees were raised off of the ground. For the "On Hands and Knees" posture participants were asked to position themselves so that their hands, knees and toes were the only points in contact with the ground, this positioned them so that the thigh was within approximately forty-five degrees of vertical and the torso was horizontal.

The activities were organised in three identical blocks where each activity was performed once in each block (each activity shown in Table 5.1 was carried out three times by each participant). Each block started with the participant sitting on a chair for fifteen seconds, before walking over to the matted area to carry out the on-the-floor postures. Before carrying out each on-the-floor posture, participants were shown a simple description of the posture while standing. Each posture was held for fifteen seconds, after which participants returned to a standing posture and read the instruction for the next on-the-floor-posture. At the end of each block, participants walked back to the chair and sat down.

The timestamps which marked the start and end of each activity were exported from the JavaScript application and stored for later analysis. Timestamps were verified using the timings extracted from the video footage. Custom written Python3 code was used to load the activPAL data files and extract sections of the raw triaxial accelerometer data for each activity. In this way, the middle five seconds of data from the fifteen seconds total recorded for each activity were extracted and stored in separate data files for later analysis. Each file was labelled according to the activity performed and the participant ID.

Table 5.1: The included on-the-floor postures and ADL.

Category	Activity
6 × On-the-floor Postures	Lying on Left Side
	Lying on Right Side
	Lying on Front
	Lying Flat on Back
	Lying on Back (Thigh Inverted)
	On Hands and Knees
3 × ADL	Stepping
	Standing
	Sitting

5.2.4 Simulated Falls

Participants were asked to simulate the nine falls shown in Table 5.2 in two nearly identical blocks (eighteen falls in total per participant), the only difference was the direction of lateral falls was reversed. The set of falls was based on the video analysis of the circumstances of falls in older adults conducted by Robinovitch et al. [82]. The most prevalent causes were found to be loss of balance, trips, stumbles, hits, bumps, loss of support with external objects and collapses. Hits, bumps and other falls involving external objects are difficult to safely simulate without increased risk of injury to participants, therefore these were not included. The most common activities leading to a fall were walking, initiating walking, standing and changing posture e.g. standing up or standing and reaching. Therefore, these activities were combined with the causes to produce the set of falls shown in Table 5.2. To allow clear identification of falls in the accelerometer data, participants were asked to stand for fifteen seconds between each fall and remain still on the floor for fifteen seconds after each fall.

For each fall, participants were shown an instruction slide using the JavaScript application, this consisted of a brief sentence describing the fall and, for all but the collapse type falls, a stick figure animation (an example stick figure animation is shown in Figure 5.3). Each stick figure animation was custom developed using TISFAT:Zero animation software [176].

The primary reason for the use of stick figures was to provide enough information for participants without enabling them to simply copy as they might if shown a video. The aim was to increase the variability in the simulations and make the tests of algorithms based on the data more robust. The two collapse type falls did not use stick figure animations, instead, participants were given free choice over how they collapsed, for example, the direction in which they fell. This was a further method used to increase variability in the data.

Table 5.2: The nine types of simulated fall with direction and landing posture.

Fall Type	**Direction**	**Expected Landing Posture**
Walking Forward LOB	Forward	Front-Lying
Trip On Initiating Walking	Forward	Front-Lying
Walking Trip With Rotation	Forward	Side / Front-Lying
Walking Lateral LOB	Lateral	Side-Lying
Standing Lateral LOB	Lateral	Side-Lying
Standing Reaching LOB	Lateral	Side-Lying
Stumble Backward Trip	Backwards	Lying on Back
Walking Collapse	-	-
Standing Collapse	-	-

Note: No direction or landing posture was specified for either of the collapses, participants were given a choice in order to add a random element, increase variability and make the test more robust. LOB = Loss of Balance.

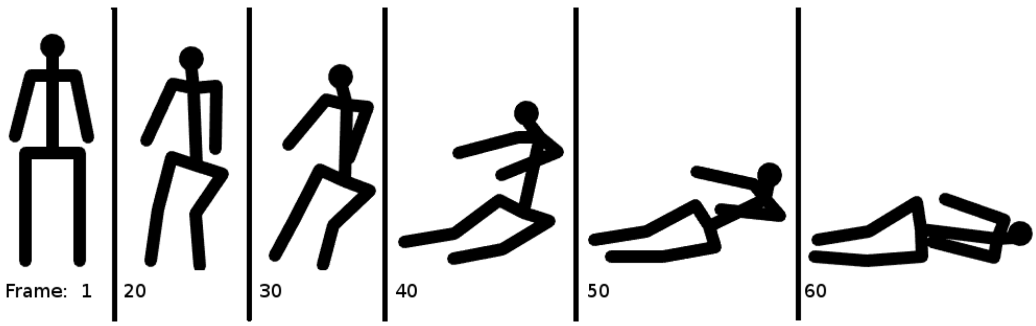


Figure 5.3: Example stick figure animation. Six stills of key frames from the 'standing lateral loss of balance' animation.

Timestamps for each fall and recovery (standing up) were exported from the JavaScript application and verified using the video footage. These were then used to extract a section of raw accelerometer data for each simulated fall starting ten seconds before impact and lasting thirty-five seconds. Each section of extracted data was labelled according to the participant ID and the type of fall before being stored for later analysis.

5.3 Posture Classification Algorithm Design

A posture classification algorithm was designed to identify periods of upright (standing or walking), sitting and lying. The posture classifier was designed as a decision tree (see Figure 5.4), building upon previous work in the field [177,178]. The first stage of the algorithm determined whether the posture was upright or sedentary, sedentary postures were then sub-classified as either sitting or lying. Orientation was used to make the decision at each node of the decision tree, the orientation of the activPAL3 axes relative to the body are shown in Figure 5.5. A one-second moving average filter was used to smooth the signal and isolate the gravitational component of the signals prior to analysis of orientation.

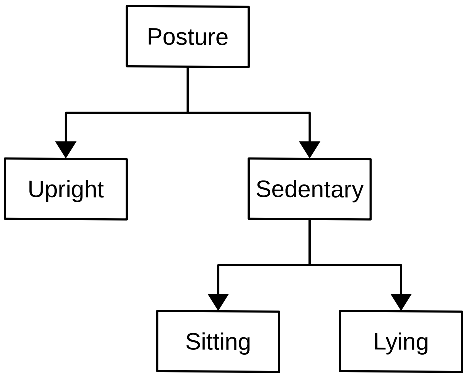


Figure 5.4: Posture classification decision tree.

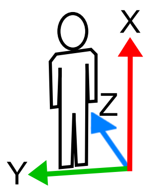


Figure 5.5: Orientation of activPAL axes relative to the body.

5.3.1 Upright versus Sedentary Classifier

A classifier was designed to distinguish between upright and sedentary postures using the tilt angle of the thigh as measured using the X-axis (Figure 5.6). When upright, the thigh is close to vertical ($\simeq$ -1 g) and when sedentary the thigh is close to horizontal ($\simeq$ 0 g) or possibly inverted (> 0 g). Therefore thresholds placed between negative one and zero g can be used to distinguish between upright and sedentary postures. Dual thresholds were used to prevent rapid changes in classification when close to the threshold. The zone between thresholds acts as a buffer, increasing the change in angle required to swap back to the previous state. The thresholds were optimised based on analysis of the data.

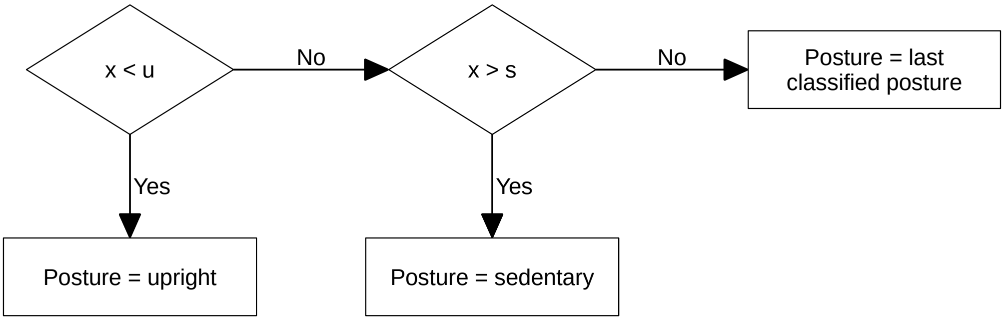


Figure 5.6: Upright versus sedentary posture classification using dual thresholds. u is the upright threshold, s is the sedentary threshold and x is the moving average filtered X-axis acceleration.

5.3.2 Sitting versus Lying Classifier

A classifier has recently been developed to sub-classify sedentary postures into sitting and lying using thigh-worn triaxial accelerometer data [171]. The classifier was designed to identify long periods of lying such as time sleeping in bed and is not optimised for detecting lying post-fall. As such, the classifier used a fairly extreme threshold on the Y-axis for thigh rotation (±65° with 0° inclination). The threshold of ±65° was calculated using an inverse sine function on the acceleration data, the true threshold is 0.906 g (sine 65°). The angle of rotation this equates to will vary depending on the inclination of the thigh in the X-axis. The angle of rotation required for the acceleration due to gravity in the Y-axis (θ) to reach 0.906 g can be calculated for any given inclination angle (ϕ) using the following equation:

$$\theta = \sin^{-1}\left(\frac{0.906}{\cos\phi}\right) \tag{5.1}$$

Using this equation we can calculate that for inclination angles (ϕ) greater than ±25° the threshold thigh rotation angle is greater than ±90° and therefore it becomes impossible to cross the threshold.

In addition to the potential lack of sensitivity of Lydens's algorithm in detecting side-lying, it is also important to consider that a faller may not roll onto their side, might fall straight onto their front or into other non-side lying postures. Therefore, Lyden's approach was adapted and extended with the aim of more sensitive and holistic detection of lying. For the new lying classifier, the thigh rotation threshold was kept and two new thresholds were added for the detection of lying on the front and postures where the knee is raised above the hip, respectively. No threshold was devised for lying flat on the back, which is particularly difficult to distinguish from sitting as the orientation is identical.

The first threshold was on the Z-axis to identify forward lean. When the Z-axis value is zero this indicates the thigh is not tilted either forwards or backwards when at a value of negative one g the front of the thigh is facing the ground. Therefore, a threshold between zero and negative one g enables the detection of forward lean and front-side-lying. The second threshold was for the identification of negative thigh inclination. When the X-axis value is between zero and one g this indicates that the thigh is inverted i.e. the knee is raised above the hip. Therefore, a threshold for the X-axis between zero and one g enables identification of postures where the knee is raised above the hip such as lying on the back with the legs bent at the knee. The three thresholds were optimised based on analysis of the data.

5.4 Optimisation and Evaluation of Posture Classifier Performance

Leave-one-participant-out cross-validation with the on-the-floor postures and ADL dataset was used to optimise and evaluate both the upright versus sedentary and the lying classifier. In each round of the cross-validation, a different participant's data were set aside for testing, with the remaining data used to set the thresholds. Through the separation of the dataset by participant, the independence between the training and testing data was maximised. The use of cross-validation allowed a more accurate estimation of the trained classifier's performance on unseen data compared to a single train-test split, because all the data, rather than a subset, was used to test the classifier.

All posture thresholds were set at either the minimum value minus ten percent of the interquartile range or the maximum value plus ten percent, depending on which was appropriate for the specific class. To set the thresholds, data from multiple postures were grouped. The upright group contained stepping, standing and hands & knees, the sedentary group contained all remaining postures except lying on back with the thigh inverted, where the X-axis values differed greatly from other sedentary postures. A side-lying group was created by combining rectified values for left and right side-lying. The forward lean and thigh inclination thresholds were found using the lying on front and lying on back with the thigh inverted posture respectively.

For comparison of lying classification results, an implementation of the classifier designed by Lyden et al. [171] was also tested. There were two changes in this implementation, compared to that of the original. In the current implementation, the upright and sedentary classifications were generated using the classifier described above (with thresholds optimised using the simulated posture dataset) instead of using the activPAL software. The twenty-second moving average filter was changed to a one-second moving average filter. The change to the filter was necessary due to the shorter periods spent in each posture during the lab-based data collection compared to free-living behaviour. This was expected to have minimal effect on the results as participants were instructed to remain still for fifteen seconds in each posture, reducing the need for filtering.

5.5 Evaluation of Pre and Post Fall Posture Detection

The ability to detect an upright posture pre-fall and a lying posture post-fall was evaluated using the simulated falls data; all falls in this dataset were from an upright to a lying posture. The pre-fall period was taken as the period between three and two seconds prior to the start of the fall and the post-fall period was taken as the period between two and three seconds after the fall. The fall event was taken as half a second before until half a second after the recorded fall time. These timings ensured participants were at rest during the periods used for posture classification.

First, the ability of the newly developed upright versus sedentary classifier to detect an upright posture pre-fall and a sedentary posture post-fall was tested. Second, three different sitting versus lying classifiers were tested to assess their capability to detect the lying period following each of the simulated falls. The first algorithm tested was the new classifier developed using the on-the-floor posture and ADL (New), the second was the algorithm developed by Lyden et al. [171] (Lyden), and the third was the newly developed classifier but using the thigh rotation thresholds from Lyden et al. [171] (Hybrid). To allow the results to be compared for each type of lying, the recorded video footage was used to label each fall signal with the post-fall posture. Post-fall posture was categorised based on the side of the body on which the participant was lying; the categories were: front, right, left, back or between two of these e.g. back-right.

5.6 Evaluation of Signal Clipping

To assess the suitability of the activPAL3's ± 2 g range, the collected fall signals were analysed for clipping within 2.5 seconds of the recorded fall time. Clipping of the signals was defined as a true acceleration value outside the range which the device can record. Clipping was characterised as either a clear clipped peak (flat top) where consecutive samples were equal to ± 2 g or a potentially clipped peak where a single sample had a recorded value of ± 2 g.

5.7 Results

5.7.1 Participants

Eight healthy volunteers (five female, three male) completed the study. Participants' age ranged from twenty-two to thirty-seven years (mean 27.8 $\pm$ SD 4.6 years), height from 1.60 to 1.83 m (1.71 $\pm$ 0.07 m) and body mass fifty-six to eighty-three kg (66.5 $\pm$ 10.3 kg).

5.7.2 Posture Classification

5.7.2.1 Classifier Optimisation and Evaluation on the Posture Dataset

Examination of the video footage revealed that in one trial of lying on the back with thigh inverted, the leg to which the activPAL was attached remained straight, this trial was relabelled as lying flat on the back. Therefore, the on-the-floor postures dataset contained twenty-five examples of lying flat on the back, twenty-three examples of lying on the back with thigh inverted and twenty-four examples of the other postures.

Across the eight rounds of cross validation on the on-the-floor postures and ADL dataset the mean (± SD) threshold to become upright was -0.812 g (± 0.014) and to become sedentary was -0.516 g (± 0.006). The mean thigh rotation, forward lean and thigh inclination thresholds were 0.509 g (±0.090), -0.808 g (± 0.063) and 0.544 g (± 0.01) respectively. Figure 5.7 shows a confusion matrix for the posture classification performance. The classifier was able to distinguish upright from sedentary with a sensitivity of one and specificity of one. Lying was distinguished from non-lying with a sensitivity of 0.742 and a specificity of one. When the implementation of Lyden's lying classifier was run on the on-the-floor postures and ADL dataset, the results were a sensitivity of 0.242 and specificity of one.

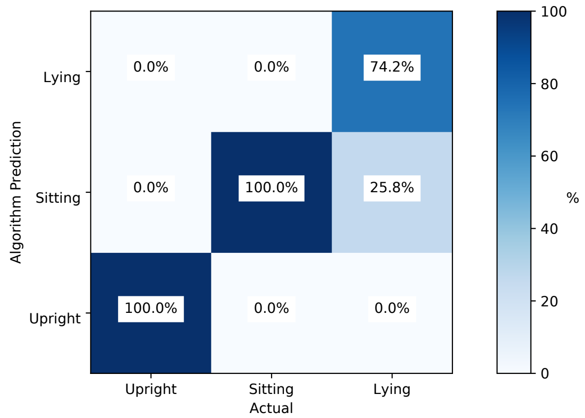


Figure 5.7: Posture detection confusion matrix.

The spread of the data for each posture and thresholds derived from the complete dataset are shown in Figure 5.8; it is these thresholds which were used in the evaluation of the algorithm on the simulated fall dataset. The plot also highlights the difficulty distinguishing standing from hands & knees, and sitting from lying flat on the back, based on thigh orientation.

5.7.2.2 Classifier Evaluation on the Simulated Fall Dataset

The developed upright versus sedentary posture classifier correctly classified the pre-fall posture as upright and the post-fall posture as sedentary for all of the simulated falls. The results of the evaluation of the ability to detect lying post-fall are shown in Table 5.3. The newly developed classifier performed the best, correctly detecting lying post-fall for 130 out of the 144 falls. The classifier developed by Lyden et al. [171] only detected lying for fifty-six

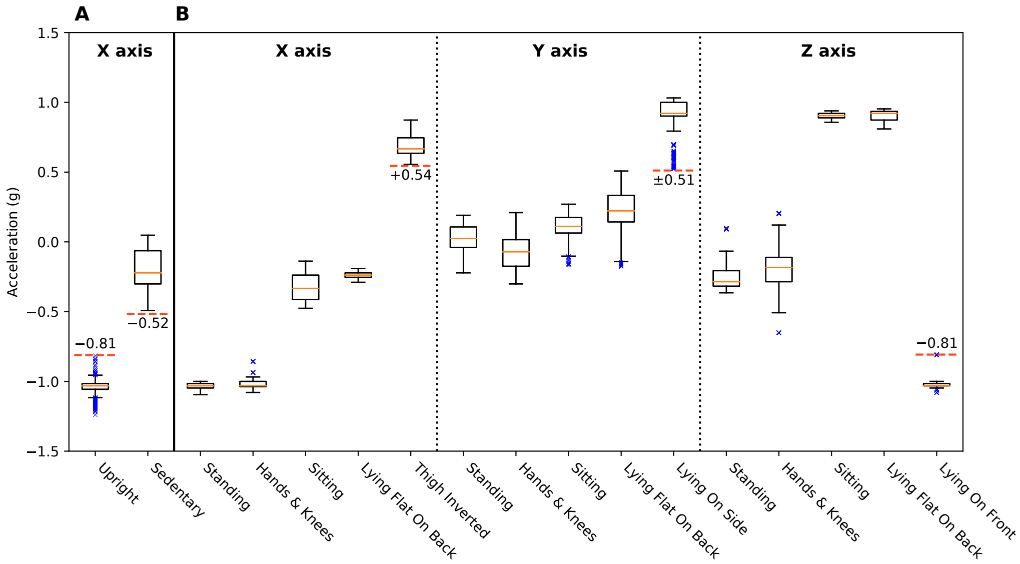


Figure 5.8: Boxplots showing A) the spread of X-axis values for upright versus sedentary and B) all three axes for standing, hands & knees, sitting and different types of lying. Thresholds are marked using dashed orange lines.

of the falls, all of which were side-lying. The hybrid classifier was able to additionally detect lying for the forty-two front-lying post-fall postures and three of the seventeen back lying post-fall postures (101 of the 144 total). For the three back lying postures detected by both the new and hybrid classifiers, the knee was raised which triggered the thigh inversion threshold, none of the cases where the thigh was flat on the ground were classified as lying.

Table 5.3: Number of simulated falls where lying was correctly detected post-fall for the three lying classifiers.

Post-Fall Lying Catagory	n Falls	New	Lyden	Hybrid
Back	17	3	0	3
Back-Right	2	2	0	0
Back-Left	1	1	0	0
Right	38	38	36	36
Left	36	36	20	20
Front-Right	6	6	0	0
Front-Left	2	2	0	0
Front	42	42	0	42

5.7.3 Signal Clipping

In forty-one out of the 144 fall signals there were clear clipped peaks, in a further 100 of the signals there were peaks of ± 2 g, suggesting potential clipping of the signal. In all instances of clipping the length of the clipped signal was less than 0.1 seconds consecutively.

5.8 Discussion

The primary aim of the study was to evaluate the suitability of the activPAL3 device for research on fall detection. Previous work on fall detection has centred on three key areas: vertical motion, impact and posture change. Methods to measure vertical motion and impact with a triaxial accelerometer have been developed previously [e.g. 99,106], and these can be applied to activPAL data. Therefore, this study focused on the classification of pre and post-fall posture using a thigh-worn activPAL3 accelerometer.

5.8.1 Posture Classification

A posture classification algorithm was developed which showed a good level of performance in comparison to the previous state of the art. The algorithm was designed as a decision tree and consisted of two sub-classifiers, one for upright versus sedentary and one to further classify sedentary periods as either sitting or lying. The algorithm was able to distinguish all recorded examples of sedentary postures from upright postures, except for the hands and knees posture where the thigh was upright. When one is kneeling with the thigh in a vertical alignment, orientation cannot be used to distinguish this posture from other true upright postures (standing and walking). The only potential method to classify on the hands and knees separately from other upright postures would be to identify and analyse the transition. Analysis of posture transitions was beyond the scope of this study as a controlled transition from standing to on hands and knees is likely to be different from a fall onto one's hands and knees.

The algorithm developed by Lyden et al. [171] to detect lying in bed, showed poor performance in distinguishing short periods of sitting from lying with a sensitivity of just 0.242 on the collected dataset. Further analysis revealed that Lyden's algorithm could not correctly classify as lying any of the example signals for lying on the front, lying on the back or lying with an inverted thigh. Through adjustment to the thigh rotation threshold and the addition of thresholds for forward lean and thigh inversion, the sensitivity of lying classification was increased to 0.742.

The thigh rotation threshold derived from the data collected during this study appears to lead to an under-sensitive classifier as twenty-six percent of lying was detected as sitting. However, this was due to an inability to distinguish lying flat on the back and sitting, the classifier was sensitive to other lying postures. Given that there is overlap between lying and sitting, in terms of thigh orientation, perfect classification is not achievable. The method used to set the thresholds was designed to ensure high sensitivity of lying classification, and the sensitivity was increased compared to the algorithm by Lyden et al. [171]. However, the distinction between sitting and lying flat on the back remains a challenge, as shown in Figure 5.8 the orientation of the thigh is identical in these two postures. If the thresholds were to be adjusted to increase the sensitivity to lying, then some sitting would be detected as lying.

When the lying classifiers were tested on the simulated fall data, the results were similar to the cross-validated results with the on-the-floor posture data. The newly developed classifier was able to detect all forms of lying except flat on the back, the classifier by Lyden et al. [171] could only detect three-quarters of the lying on the side and none of the other lying subtypes. The thresholds developed by Lyden et al. [171] resulted in a different sensitivity for left and right-side-lying, where the sensitivity to lying on the right side (the thigh on which the activPAL device was attached) was greater than for lying on the left side. This was likely due to the incline of the thigh furthest from the floor; when the knee rests on the floor the upper thigh is at an incline which increases the rotation required to trigger the threshold on the Y-axis (see Figure 5.9). Where the incline of the thigh with respect to the floor is greater than twenty-five degrees (0.42 g) it is not possible for the acceleration due to gravity to exceed the threshold on the Y-axis of 0.906 g.

The new, more sensitive, thigh rotation thresholds devised based on the on-the-floor posture data allowed all side-lying to be classified and in the limited testing did not lead to misclassification of sitting as lying. However, in this study all participants sat on the same chair with their feet on the floor, therefore only a subset of the possible sitting postures were tested. In the real-world misclassification of sitting as lying is likely as the threshold of ± 0.51 g, which equates to thirty degrees thigh rotation when the thigh is parallel to the ground, could feasibly be exceeded when sitting. In addition, in the real-world the

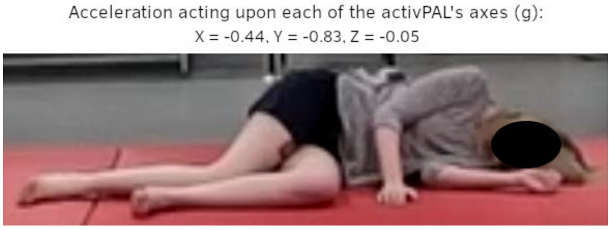


Figure 5.9: Lying on the left side post-fall. The incline of the thigh with respect to the floor results in a lower acceleration due to gravity on the activPAL's Y-axis compared to if the thigh had been parallel to the floor. Despite the participant being fully rotated onto their left side, the acceleration due to gravity on the activPAL's Y-axis is less than the threshold devised by Lyden et al. [171] ($Y > 0.906$) and so lying was not detected when their threshold was used.

device may be less precisely aligned with the midline of the anterior aspect of the thigh, effectively reducing the thigh rotation required to cross the threshold. Over a period of a few days wear, the attachment of the activPAL device to the thigh may loosen slightly and allow the device to slip; due to the curvature of the thigh, a small shift in placement could have a significant effect on the accuracy of sitting versus lying classification.

The algorithm developed by Lyden et al. [171] worked for long periods of lying because if the thigh rotation threshold was crossed at any point during a sedentary period, the whole period was classified as lying. This allowed a relatively extreme threshold to be used to maximise specificity without substantially limiting the sensitivity. However, their algorithm did not achieve perfect classification of "in bed" lying periods, the sensitivity was 0.97 and the specificity was 0.93. To detect short periods of lying, the approach proposed by Lyden et al. [171] cannot be used as the wearer of the device may not roll fully onto their side. Instead, the thresholds must be adjusted to reduce the amount of rotation required to be detected as lying, however, doing so would reduce the specificity.

The results showed that the only type of lying that simple thresholds can be used to robustly detect is lying on the front. Lying flat on the back could not be distinguished from sitting as the thigh orientation is the same. Lying on the side could only be consistently detected with the use of a thigh rotation threshold of 0.52 g, which is likely to lead to misclassification of sitting as lying; when the rotation threshold was increased, side-lying was misclassified as sitting. Hence, it does not appear possible to robustly distinguish between short periods of sitting and lying based on simple thresholds for the orientation of the thigh. Since fall detection, rather than lying detection, is the focus of this thesis, further development of lying detection will not be conducted and lying classification will not be used in the study which follows.

There is a clear trade-off, in terms of posture classification, between placement on the thigh and the torso. The torso has been the more popular choice for fall detection [8], in part due to its proximity to the centre of mass and partly as a torso-worn accelerometer can be used to robustly detect lying postures. The detection of a change in torso orientation, indicating a transition from upright to lying, has been used to reduce false positives [e.g. 102,106]. However, since it is possible to fall into a sitting posture, this approach may also lead to missed falls. Conversely, a thigh worn device can robustly detect sedentary postures, but not robustly distinguish between sitting or lying.

The ability to detect lying may be a useful feature for fall detection, but the findings of this study indicate that lying post-fall cannot yet be detected reliably enough for use in fall detection with a thigh-worn device. The upright versus sedentary posture classifier had a sensitivity and specificity of one in detecting an upright posture pre-fall and a sedentary posture post-fall. Therefore, transitions from an upright to a sedentary posture can be detected reliably with a thigh-worn accelerometer and could be used as part of a fall detection classifier.

The resting posture following a fall could be either sitting or lying, but will certainly be some form of sedentary posture. Analysis of video recordings of falls suggests that eighty percent of falls occur from an upright posture and that in forty percent the faller comes to rest in a sitting position [81,82]. Therefore, a classifier that only detects a fall when lying is identified would miss a significant proportion of falls. These findings indicate that the ability to distinguish upright and sedentary postures is of greater importance than the sub-classification of the sedentary class. Since the distinction of upright and sedentary postures is a strength of a thigh-worn device, these may be more suitable for detecting fall-related posture changes than a torso-worn device.

5.8.2 Suitability of the activPAL3 Device

The activPAL3 device was able to record acceleration signals during the simulated falls without any reported discomfort from participants. The method of attachment of the device to the thigh using PALstickies allowed the device to be removed easily due to the relatively low adhesion to the skin. The ability to remove the device easily is desirable when used with older adults who may have fragile skin with an increased risk of damage when the device is removed. However, the device became loose from one participant's leg during data collection, therefore PALstickies may not be suitable for long-term monitoring as there is a risk of the device falling off, causing inconvenience and potentially a loss of data. Alternative methods of attaching the monitor to the thigh need to be considered before the start of real-world data collection.

The majority of recorded signals from simulated falls showed potential clipping of the signal. Clipping of the signal prevents analysis of the magnitude of the impact peak due to the true acceleration values not being recorded. Therefore, a range of greater than ± 2 g is needed for comprehensive analysis of the impact peak. For future research, it must be considered whether a different device is more suitable for the study of falls or whether the advantages of the activPAL3 outweigh its limitations.

The occurrence of clipping in real-falls remains unknown but may be less common due to the faller trying to save themselves from falling and minimise injury rather than deliberately falling, as in the simulations. Natural reactions to falling combined with a furnished environment may potentially result in multiple smaller impacts or slower, lower impact falls as a result of grabbing onto furniture. However, analysis of real falls is needed to establish if this is the case.

The activPAL3 device was initially selected due to its small size, good battery life and because it had a proven track record in monitoring movement of older adults. While the limited sensor range may place constraints on the analysis of recorded fall signals, on balance it remained the preferred device. The advantages of the activPAL3 as outlined above should facilitate monitoring over extended periods and the collection of enough data for research into the characteristics which make falls unique. At the time of data collection (2015) there was no known device which fulfilled all criteria; one with a greater sensor range but reduced battery life or larger size, may impact participant comfort and result in reduced participation, higher withdrawal and ultimately fewer data. Technology continually evolves and therefore, the most suitable device continually changes. Future studies should carefully consider which device to use.

5.9 Conclusion

In this study, a significant step forward has been made in the classification of lying postures using a thigh worn accelerometer. Through analysis of thigh orientation during a series of on-the-floor postures, understanding has been gained of the likely position of the thigh following a fall. While the sensitivity of lying detection was improved compared to the algorithm developed by Lyden et al. [171], in real-world use this is likely to be at the cost of specificity. The detection of short periods lying appears to be more challenging than expected based on the simplicity of Lyden's algorithm and their positive results for identifying lying in bed. There are clear challenges in detecting short periods of lying, such as those which may occur post-fall, and further research is needed in this area before the detection of lying with a thigh-worn accelerometer can be used in fall detection. However, the algorithm developed to classify posture as upright or sedentary was shown to be robust and could be used in fall detection.

Despite the limitations of the activPAL3's ±2 g range, on balance, the device is suitable for the recording and study of real fall signals due to its track record in continuously monitoring the movement of older adults. To record falls a large volume of real-world monitoring is required, for this to be possible the device used needs to be comfortable to wear and have good battery life. The activPAL device has been shown through its use in twenty-four seven monitoring of older adults in previous studies to meet these requirements. The limitations of the activPAL3 were deemed not to outweigh its benefits.

Chapter 6

Collection of Real-World Fall Data

6.1 Introduction

Real-world data is critical for fall detection research as laboratory simulations of falls have been shown not to be representative of the real-world (Section 3.4). Real-world data is, therefore, essential to identify new ways to detect falls and only tests of fall detection technology using real-world data can give realistic estimations of performance. However, there has been a lack of research in the field of fall detection which has used real, naturally occurring falls (Chapter 4). The studies which have been conducted have typically used an extremely small number of falls. The review of methods to test fall detection technology with real-world data found that only twenty-two studies had been conducted (Chapter 4). In addition, the number of falls included was small with seventy-five percent of studies using less than thirty fall samples.

Where real-world data has been used, the focus has been on tests of fall detection technology and performance has been poor (Section 3.6). There is a need for research to identify new methods to distinguish between falls and other movements so that an acceptable level of performance can be achieved (Section 3.7). However, only one study has been conducted which has compared features of real fall signals to those of other movements [114], and this study did not find any features which could yield performance beyond the current state-of-the-art. There is a need to carry out further research to compare fall signals to other movements so that the reasons why previous fall detection technology has not performed at an acceptable level can be understood and new methods to improve performance can be identified. To do this requires a real-world dataset and so a project was carried out to collect a real-world dataset of falls and activities of daily living comparable in size to the largest used in previous studies.

To record a sizeable real-world dataset, it was critical to partner with an organisation who worked with fall-risk older adults and who were willing to assist with recruitment. To this end, a collaborative partnership was established with Four Seasons Health Care (FSHC), an independent health care provider which runs over 250 care homes across the UK and provides care for over 13,000 people. Participants in this study were recruited from, and all data were collected in, FSHC's care homes situated across the north of England and Scotland. The project was designed by the University of Salford researchers, however, participant recruitment and data collection were managed, under the guidance of researchers, by each participating care home.

The project aimed to recruit 250 participants for two months of data collection and record 100 fall signals. A total of 100 recorded fall signals would be in line with the largest datasets used in previous studies [21,114,122] and would allow an extensive set of features to be tested, without excessive risk of type I errors. The two month monitoring period was chosen to maximise the chance of recording 100 falls while still keeping the participant recruitment target feasible. Assuming a similar fall rate to previous studies of approximately 100 days per fall [19–21], the combination of 250 participants and a two-month monitoring period would be sufficient to yield 150 falls. Therefore, there was allowance for a slightly lower rate of falls than predicted, participants withdrawing before the end of the two months or lower than expected participant recruitment.

6.1.1 Study Design

The study was designed as an observational study in order to maximise ecological validity. Two months of accelerometer data were collected for each participant using a wearable device attached to the thigh of participants. Participants were free to follow their usual daily routines, no activities were prescribed as part of the study. Fall signals were recorded as and when participants naturally fell and were wearing the device, records of when falls occurred were retrieved from the existing incident reporting system used by the homes. The only change to the daily routines of participants and their care staff was the attachment and replacement of the accelerometer device which was routinely replaced weekly and temporarily removed for bathing.

6.2 Collection of Real-World Fall Signals

The study was approved by both the University of Salford's College of Health and Social Care Research Ethics panel (reference HSCR 15-109) and the UK Social Care Research Ethics Committee (reference 17/IEC08/0019) (see Appendix D). To ensure that the care home residents' confidential records were protected, data shared with the university were limited to only that which was deemed essential. The data shared consisted of identification numbers for participants, fall records for participants during their participation and dates and reasons for withdrawal where appropriate. All data were anonymised prior to the university gaining access, each participant was known only by their identification number and no personal information such as name, date of birth or gender were shared. The sections which follow provide details of participant recruitment and the protocol for data collection.

6.2.1 Selection of Participating Care Homes and Identification of Potential Participants

Selection of homes to take part in the study was primarily the responsibility of FSHC, however, the criteria for selection were agreed following discussions with the University of Salford. Care homes from the North West of England, North East of England and Scotland were considered for participation. The criteria for the selection of homes were designed to maximise the potential number of participants and the likelihood of capturing falls given the available resources. Only a handful of homes could participate simultaneously as each added a significant workload to the management of the study. Staff at each home needed to be trained and each home needed to be contacted regularly during the study to ensure any issues were raised and dealt with promptly. Therefore, the homes which had high numbers of recent fallers were prioritised. To minimise the chance of unreported or inaccurately reported falls, only homes which FSHC identified as consistently good at completing incident reports for falls were included.

A number of tools to assess fall risk have been presented in the literature (Section 2.3.2). It would be impractical to screen all residents with any of these tools, therefore existing data from the FSHC system was used to identify residents with elevated fall risk. Research has shown that a history of falls is the strongest predictor of future falls [62,63,179], thus recent fall history was used as a method to identify potential participants. Based on the two-month duration of data collection, the cut-off for inclusion was set at two falls within the previous three months. If falls occurred at that rate or higher during data collection, then one would expect participants to fall at least once during the study on average.

The FSHC incident database was queried by their data manager for recent recurrent fallers. A shortlist of homes to approach was agreed following discussion between the data manager, the regional management and the University of Salford researchers. The regional management provided guidance on the suitability of homes to take part in the study and had the final say on which were included.

The care homes were first introduced to the project by the regional management and FSHC's head of care projects. Next, the study was explained to the home manager during a conference call with both a University of Salford researcher and FSHC's head of care projects. Ahead of the call, the home manager was sent the document pack which contained the information documents and forms needed during the recruitment (Table 6.1). During the conference call, the background to the study and what it involved were explained to the home manager and training was provided on the recruitment process. Once the home manager had received training on participant recruitment, they were sent the list of identified recent recurrent fallers and began the recruitment process. The home managers were responsible for disseminating information about the project and providing training on the recruitment process for their staff. Home managers were given contact details of both researchers at the University of Salford and those within FSHC who could answer any queries.

6.2.2 Participant Recruitment

Recruitment of participants was managed by the participating care homes, under the guidance of researchers from the University of Salford. Before recruitment could begin, the home managers, with the support of their staff, decided which of the identified recent recurrent fallers were suitable to participate. The decision of suitability to participate was based on the exclusion criteria and their knowledge of the individual's health status. The primary reasons for exclusion were: (1) existing skin conditions (e.g. psoriasis or eczema) which could be affected by the dressing used to secure the accelerometer device and (2) the inability to walk (dependant on a wheelchair). Those who could not walk were excluded as the focus of the research was falls from upright rather than sedentary postures.

Pathways and supporting documents for the recruitment of participants were developed in collaboration with FSHC. Central to the recruitment process were the issues surrounding participants' mental capacity to provide informed consent. The recruitment process used during this study was aligned to FSHC's existing policies on the assessment of mental capacity and decisions on behalf of those without capacity. In accordance with the Mental Capacity Act, 2005 potential participants were presumed to have capacity unless it could be proven otherwise. Before a decision was made potential participants were given all appropriate help to understand what was asked of them.

There were two pathways: pathway A was used where potential participants had the mental capacity to understand the study and provide consent; pathway B was used where care home staff had reason to doubt mental capacity. In the first stage of recruitment care staff discussed the study with potential participants and made an assessment as to which recruitment pathway to follow based on the potential participant's ability to understand the study. If during the recruitment process staff deemed that a potential participant should be on the other pathway, they were free to swap pathways. Figure 6.1 shows the process followed in the recruitment of participants, which includes both paths. An overview of the supporting documents is presented in Table 6.1 and copies of the documents can be found in Appendix E.

6.2.2.1 Pathway A

Following a discussion about the project with a potential participant, if staff had no reason to doubt a potential participant's capacity, written information about the study was provided (Appendix E.2). Potential participants were given at least one day before being asked to decide whether to participate. If they wanted to participate in the study care staff provided an informed consent form for completion (Appendix E.6).

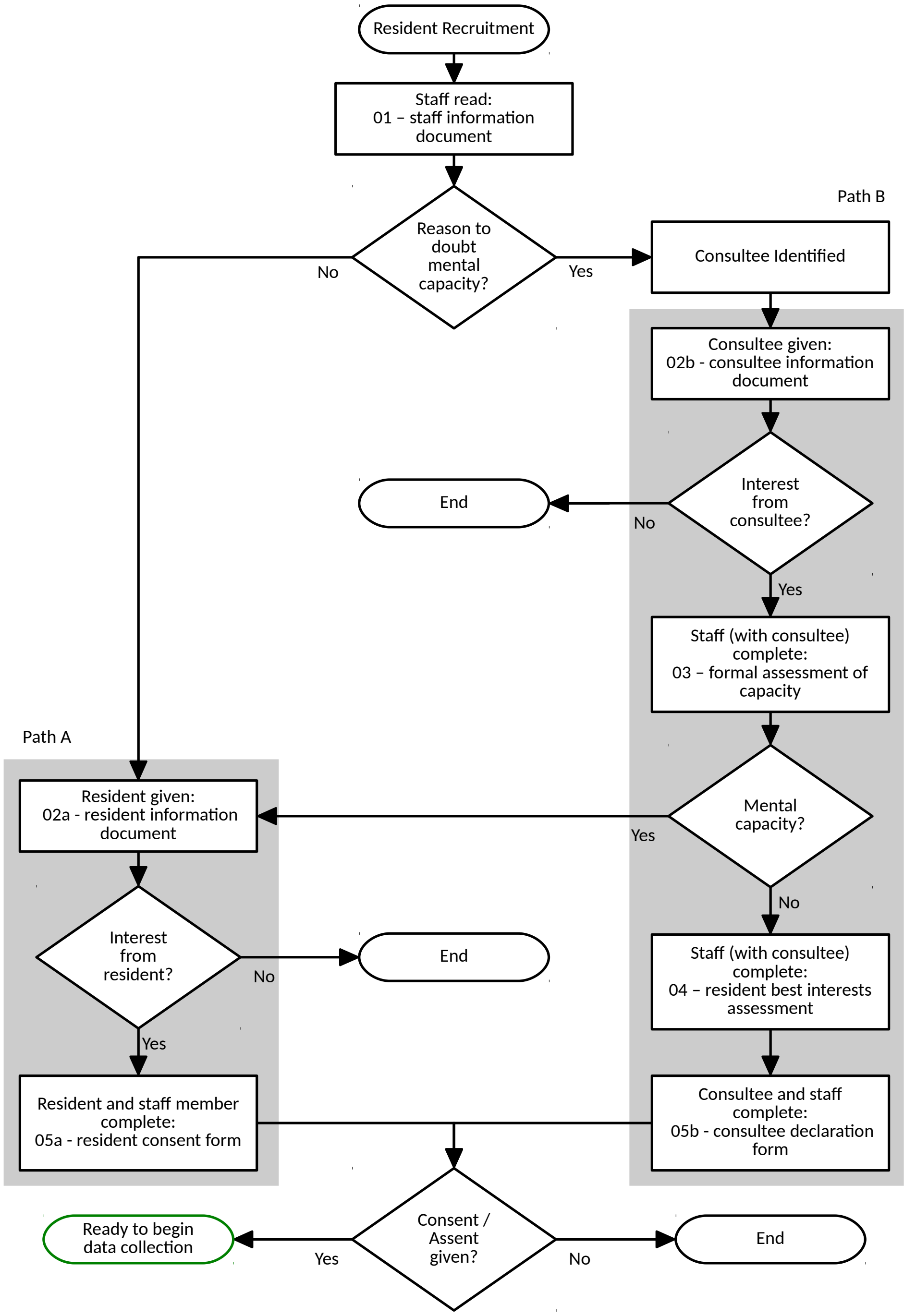


Figure 6.1: Overview of the recruitment process for care home residents.

Table 6.1: Documents used during recruitment of participants.

Document	Description
Project Information	Overview of the project and content of the document pack. Explained each step in the recruitment process.
Staff / Participant / Consultee Information	Explanation of the study and what participation involved, how the data will be used, procedures for withdrawal and complaints. The three versions differed on the cover letter and the wording used to refer to participants, all information on the main document was identical.
Assessment of Capacity	Form used to record assessments of mental capacity concerning understanding the study and making a decision on whether to participate.
Determination of Best Interests	Form used to record the process of reaching a decision as to whether participation was in the interests of an individual.
Participant Consent Form	Form used to record participant consent to take part.
Consultee Declaration Form	Form used to record consultee consent on behalf of a person who lacked the capacity to make the decision.
Training on Mental Capacity Video	A video which explained why capacity assessments were needed, when they should be carried out and the procedure for carrying out the assessments.

Note: These documents were developed for this project in collaboration with FSHC. Copies of these documents can be found in Appendix E.

6.2.2.2 Pathway B

Where staff had reason to doubt a potential participant's capacity a consultee was identified and staff discussed the study with them and provided them with an information document. The consultee could be one or more of the following: anyone previously named by the potential participant, known carers, close friends and relatives, or the legal power of attorney. If following discussion with the potential participant and their consultee, there was interest in participating, a formal assessment of capacity was carried out and documented (Appendix

E.4). If the assessment of mental capacity showed the potential participant had the capacity to provide informed consent, they were transferred to pathway A. If a potential participant was deemed not to have capacity an assessment was carried out to determine if participation was in their best interests (Appendix E.5). The decision of whether participation was in a potential participant's best interests was based on several factors including: (1) whether they, or someone similar to them in future, would benefit from the research, (2) the views of appropriate persons following consultation. Where participation was deemed to be in the potential participant's best interests, their consultee then provided informed assent (Appendix E.7).

The forms to record assessments of capacity and determination of the best interest of potential participants were adapted from those routinely used by FSHC. The staff who conducted these assessments were trained to do so by FSHC and were familiar with the process, having previously carried out these assessments for other purposes. To provide additional support, FSHC produced a video which explained the process and why it was needed for the study (the video is available at youtube.com/watch?v=2BV6KjofPhg).

6.2.3 Protocol

Participants' movements were recorded using a wearable accelerometer for a total of two months in blocks of seven to ten days. The length of recording was dictated by the battery life of the monitoring device and the breaks between recordings were due to the retrieval of devices from the care homes and the delivery of replacements. Staff were asked to record the date and time whenever the device was attached or removed using a form provided (Appendix E.9). Before data collection began within each home a researcher from the University of Salford visited the care home to train staff. During training, staff were shown how to attach the device to the thigh and how the device needed to be positioned. The training also covered the recording of when the device was attached and removed, safeguards for those with cognitive impairment, the withdrawal procedure and the importance of accurately recording falls.

6.2.3.1 The Monitoring Device

As in the previous study (Chapter 5), participants' movement was recorded using an accelerometer attached to the thigh. The device used in this study was the activPAL3

Micro™, a smaller and lighter, but otherwise functionally identical, version of the activPAL3C™ used in the pilot study (Chapter 5). The smaller device was selected to maximise participant comfort; due to the lighter weight (approximately 10g), the micro model is less noticeable during daily activities. To provide water resistance and increase hygiene, a disposable nitrile cover was used, Tegaderm™ medical dressing was then used to attach the device to the thigh of participants. Figure 6.2 shows how the activPAL3 was attached to the thigh of the participants.

The Tegaderm dressing provided additional waterproofing and in combination with the nitrile cover allowed participants to shower without removing the device, however, the device needed to be removed if the thigh was to be submerged. Care staff were asked to check the dressing every two days and replace it if coming loose, otherwise the dressing was changed after five days. To minimise the risk of irritation caused by prolonged wearing of the device, every five days the device was moved to the opposite leg.

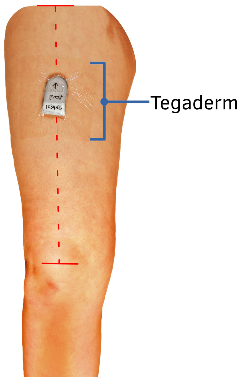


Figure 6.2: The attachment of activPAL3 Micro accelerometer to the thigh using Tegaderm dressing. The device was covered with a nitrile sleeve and attached on the midline anterior aspect of the upper thigh. The participant ID and indicators of the correct orientation were written on the front of the nitrile sleeve. The instructions given to care staff on how to attach the device can be found in Appendix E.8

The devices were sent to care homes using a next day delivery postal service along with a supply of Tegaderm and a pre-addressed return envelope. A device for each participant in the home was programmed with their ID number, a recording start time and recording duration. Prior to dispatch, the nitrile sleeve was placed over the device and sealed with surgical tape, the participant ID number was then written on the front. Devices were typically set to start recording the day after dispatch at five o'clock in the afternoon as they should have been received by midday. After the devices had finished recording the homes were asked to return them; only once the devices had been received were replacements sent. This delay in sending replacement devices gave participants at least forty-eight hours break between recordings and ensured data could be inspected for issues before further data were collected.

6.2.3.2 Fall Reporting

Falls were recorded using FSHC's existing incident reporting system as was standard practice in the homes. Periodically throughout the study, FSHC's data manager queried the system for records of participants' falls which had occurred during the study. All fall records were anonymised before being sent to the University of Salford, with participants only identifiable by ID number. The fall reports contained the following information:

- Incident date and time
- The room in which the fall occurred (e.g. bedroom or corridor)
- The subcategory (one of: fall from standing, fall from a chair, fall out of bed, found on the floor)
- The level of harm caused (one of: no harm, minor, moderate, major)
- Injury code (one of: none, cut, abrasion, bruise, shock)
- The body part injured
- Description of the fall

6.2.3.3 Safeguards for those with Cognitive Impairment

Care staff were asked to closely monitor participants who had cognitive impairment and ensure any signs of discomfort or rejection of the device were recorded using the provided form (Appendix E.10). Signs of discomfort could, for example, include: removing the device, fiddling with the device, reluctance for the device to be attached to their thigh, any expression of discomfort when the device was removed. Signs of discomfort could be highly individual, so care staff were asked to use their professional judgement rather than follow prescribed criteria. The home managers were responsible for following up with care staff and liaising with researchers to identify appropriate action. Participants could be withdrawn by the home manager if they believed participation was having a negative impact on well-being.

6.3 Data Management and Processing

To handle the relatively large and complex set of data generated during the study, data were managed and processed using custom software developed using Python3 combined with additional open-source packages. The sections which follow describe how the data were managed and processed and how custom software facilitated this.

6.3.1 Data Management

The activPAL recordings were stored on an encrypted drive along with an SQLite3 database which contained the metadata, Table 6.2 provides a description of the tables contained in the database. Using relationships between tables all recordings and falls were linked to participants which in turn were linked to locations. Data were added to, and retrieved from, the database using custom software written using Python3 with the SQLAlchemy package.

Table 6.2: Tables contained in the database.

Table	**Description**
Locations	The name and contact details of each care home.
Participants	The participant information (e.g. location ID, start and end dates of participation, reason for withdrawal).
Recordings	Contained metadata (e.g. start date-time, stop date-time, participant ID) for the activPAL device recordings and the file location.
Falls	Contained the details of the falls retrieved from the fall reports.

Location and participant information were read from tabular data provided by FSHC and, following a check by a researcher, added to the database using a custom software module. Accelerometer recording metadata were ingested by scanning the files and extracting data from their header, the SHA1 hash (a fixed-length identifier) was calculated from the contents of each recording and used as the recording ID. A check that the file had not already been ingested was performed by comparing the SHA1 hash of the data with those already in the database. Each recording's header contained the participant ID as this was entered when the device was programmed, therefore each recording was automatically linked to a participant record in the database at the point of ingestion. The fall reports were exported in tabular form from the care home's data management system by their data manager (see Table 6.3 for an example). A software module was written to read the received data and populate the database.

Table 6.3: Example fall report.

Participant ID	12
Setting	DINGRM (Dining Room)
Fall Subcategory	Fall from Standing
Level	Incident without harm
Incident Date	18/11/2016
Incident Time	2200
Injury Code	NULL
Body Part Code	NULL
Description	Resident got up from the chair they were sitting in, lost their balance and fell.

6.3.2 Fall Signal Identification

To allow recorded accelerometer data to be used to assess fall detection performance, the falls within it needed to be identified accurately. The only information available to do this was the incident reports retrieved from the care homes' incident reporting system, however, these reported fall times might not be accurate. There are several reasons for a discrepancy between the reported times and the timestamp of the accelerometer data for the fall, these include:

- Delay in completing the incident report, due to prioritisation of resident care, leading to recall error and approximation in the reported time
- Unwitnessed falls where reported time was reliant on the faller's recall, which could be inaccurate due to cognitive impairment, and therefore the time could only be estimated
- Synchronisation of the activPAL device clock and the reporter's clock

To ensure that the data labelled as a fall signal was a recording of a fall, it was important to verify the reported fall times. The only method that could be used to do this was a visual inspection of the raw accelerometer signals, as no other data were available. To carry out such analysis it was necessary to know what a real-fall signal recorded using an accelerometer looked like. However, very little analysis of accelerometer signals from real-falls had been carried out previously. The literature provided no clear method to carry out this analysis as previous studies had not clearly described their processes and no consensus had been established on the best approach (see Section 4.3.4).

The approach used in the current study was based on that used in the FARSEEING project [170]. The FARSEEING project's method was identified as the most suitable approach on the grounds that the consortium which devised it included many of the leading researchers in the field. However, details of the FARSEEING project's approach were not published until October 2016, by which point the current project had been running for ten months. The degree to which the FARSEEING fall signal processing method could be followed was therefore limited and alterations were made to account for the resources and data available. The method described below is the same as that used in the FARSEEING project, except where explicitly stated.

Two experts independently examined the sensor signals and the fall reports to identify each fall signal. The fall time was identified as the point of impact, which presented as a rapid increase and decrease in the resultant acceleration. Where no impact signal was observed, the point at which posture changed was taken as the fall time. In recognition that one cannot be certain of the location of the falls, each researcher also recorded their confidence, on a ten-point scale, that the identified signal was the fall described in the report.

The FARSEEING project used a four-point scale, based on whether the reported pre-fall activity and post-fall orientation matched the signal and how close the identified time was to the reported time. The FARSEEING project included information gathered from interviews with the fallers which allowed any information missing in the original report to be collected. Such interviews were not possible during the current collection, due to the resources available. As a result, the level of detail varied and often the activity at the time of the fall and post-fall orientation were not recorded, especially for unwitnessed falls. Hence, in the current project, a subjective scale was used on account of the varying level of information available.

In the FARSEEING project, where the two experts disagreed on the fall signal, a panel of experts examined and discussed the signals and tried to reach a consensus. In the current study, only two researchers had the expertise to identify the fall signal. Therefore, in cases where there was disagreement, they met to discuss the fall signal and attempted to reach a consensus, in place of the panel meeting. In the absence of a consensus the fall was marked as unverified. Where the researchers independently identified the same signal as the fall, the confidence in the identified signal was reassessed in the consensus meeting.

To guide researchers through the fall identification process and to provide access to the information required at each stage, custom software was developed. The software was designed to provide an interface between the user and the data, to prevent accidental changes and hide all but the required information needed for the current task. The information presented to researchers by the software is summarised in Table 6.4. Data were fetched directly from the SQLite database described in section Section 6.3.1 and all results were written back to the database by the software. Further information on the fall signal identification software can be found in Appendix F.

Table 6.4: Information presented to researchers during fall time verification.

From Fall Report	**From Accelerometer**
Time	X, Y, Z-Axis Signals
Description	Resultant Acceleration
Injuries	
Location	

Each researcher was assigned an ID which they entered each time the software was loaded, all results were linked to this ID so that work was traceable. The ID also allowed the software to query the database for falls which the current user had not yet verified and which had not been verified by two researchers. The software randomly selected one of the returned fall IDs and fetched the raw signal data and information from the fall report. Aided by the software, researchers followed the process shown in Figure 6.3.

During the first phases where researchers worked individually, the software hid all existing results from researchers. During phase two where researchers met to resolve any disagreement, the software showed the previous results to facilitate the discussion. However, to minimise bias no information about which point was marked by which researcher was available during the meeting. During the meeting, the researchers followed the same process as in phase one (Figure 6.3). If researchers could not agree the fall was recorded as unverifiable. Where researchers had agreed on the fall time in phase one, the confidence was updated following discussion in the phase two meeting.

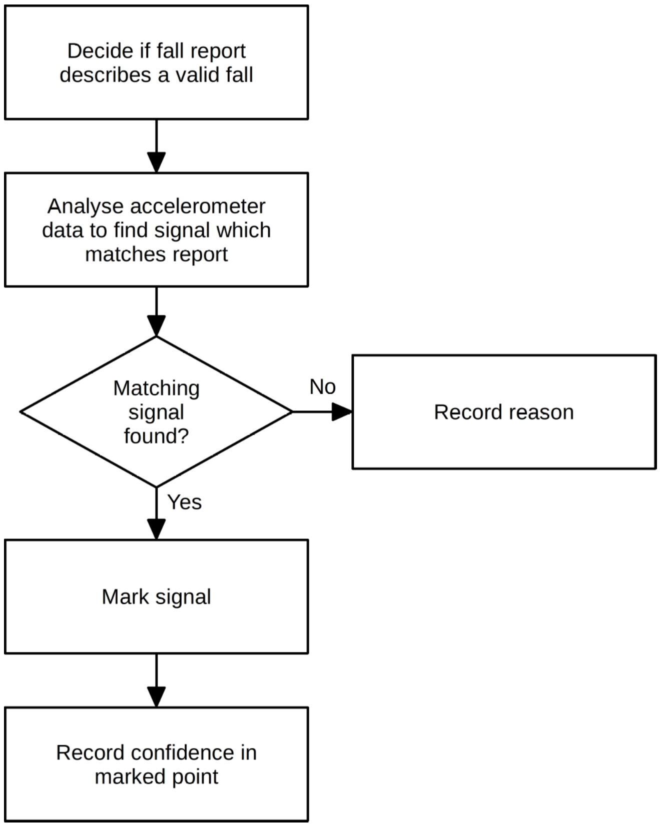


Figure 6.3: Fall verification process flow chart.

6.4 Results

Forty-five residents of FSHC homes provided consent and took part in the study. Participants were recruited from seventeen care homes with a mean and standard deviation of 2.65 $\pm$ 2.57 participants from each home. Fifteen participants completed the two-month study and thirty withdrew or were withdrawn; the reasons for withdrawal are shown in Table 6.5. Where multiple activPAL monitors assigned to a participant were lost, and following consultation with care staff, participants were withdrawn. The reason for withdrawal in these cases was to prevent further loss of hardware and because the loss of multiple monitors was a potential sign that the monitor was causing discomfort and the participant was removing it.

Table 6.5: Reasons for participation ending.

Reason for the End of Participation	**N Participants**
Completed the two-months	15
Deceased	2
Discharged from home	7
Did not want to continue to wear monitor	4
Multiple monitors lost	7
No reason given	10

Note: Data were collected from forty-five particpants, thirty withdrew from the study before two-months of data collection had been completed and fifteen completed the two months.

Due to technical issues, the fall records for three participants could not be retrieved and so their data could not be used for fall detection research, thus data from forty-two participants were usable for fall detection research. A total of 218 recordings were collected from the forty-two participants with a total duration of 1,919 days. Ninety percent of recordings were between seven and ten days in duration with a mean of 8.80 ± 1.67 days. The median total length of recordings per participant was thirty-three days with an interquartile range of 17.94 to 54.42 days.

Staff were asked to record dates and times when the device was attached and removed from the participants' thighs. However, care staff reported that participants sometimes removed the device and the staff did not know when. Due to a high workload staff reported that they did not always record the time immediately and so were unsure of the accuracy of the reported times. In addition, not all forms were completed and some were lost in the care homes and not returned. Thus, the records of wear time may be inaccurate and incomplete and cannot be relied upon in the removal of non-wear accelerometer signals.

A total of forty-seven falls from twenty-three participants were reported during the study, nineteen of the participants did not fall. Thirty-two of the reported falls occurred during periods where the device was recording and fifteen occurred during periods when the device was being exchanged through the post. Table 6.6 shows the full results of the fall identification process. Of the thirty-two reported falls which were potentially captured, four were deemed invalid. In each of the reports deemed not to be a valid fall, an intervention by care staff to assist the participant to the floor was clearly described, they were therefore not a natural fall (see Table 6.7).

Eight out of the thirty-two falls could not be identified in the accelerometer signals by the consensus of two expert researchers. In six cases the fall occurred in a period identified as non-wear as the device was not moving and in two cases no signal which matched the description could be found. In one of the falls where no signal which matched the description could be identified, the participant was found on their knees by care staff, a posture which is hard, if not impossible, to distinguish from standing in the accelerometer signals. For the other fall where no matching signal could be identified, the participant attempted to get out of the chair by climbing over the hand rest, as a fall from sedentary the posture transition would be less distinct in the signals compared to a fall from an upright posture. For six of the falls, both researchers independently concluded they could not be identified. For two of the falls, one of the researchers marked a fall during the independent assessment and the decision that the fall could not be identified was reached following a consensus meeting.

The twenty falls which were identified in the data are summarised in Table 6.8. Figure 6.4 and Figure 6.5 show example fall signals with the identified point of the fall marked. Of the identified falls ten occurred in bedrooms, three in bathrooms, three in corridors, two in day rooms and two in dining rooms. Eleven of the falls were reported to be from standing, one from a chair and in eight cases staff reported the participant was found on the floor and the circumstances could not be established.

For seven out of the twenty falls which could be identified, both researchers independently marked the same sample in the signal as the fall-related impact (see Table 6.6). For a further five of the falls, the points marked were within five seconds of each other, the median difference between researchers was 0.62 seconds with an interquartile range of zero to fifty-four seconds. The median difference between the final marked point and the reported times for the twenty identified falls was six minutes and 25 seconds with an interquartile range of 2:47 to 14:23 (minutes:seconds). All but one of the points marked during the consensus meeting were within one second of one of the originally marked points. The confidence in the signals identified as the falls following the consensus meeting ranged from three to ten out of ten with a mean and standard deviation of 7.65 $\pm$ 2.08.

Table 6.6: Results of fall signal identification.

Fall ID	Round	Valid	Identified	Unidentified Reason	Identified 🕒	Confidence	Reported 🕒
1	Researcher 1	True	True	-	07:19:19	4	07:00
	Researcher 2	True	True	-	07:19:19	6	
	Final Decision	True	True	-	07:19:19	8	
2	Researcher 1	False	-	-	-	-	10:25
	Researcher 2	False	-	-	-	-	
	Final Decision	False	-	-	-	-	
3	Researcher 1	True	True	-	22:10:28	6	01:30
	Researcher 2	True	True	-	01:26:06	4	
	Final Decision	True	True	-	22:10:28	6	
4	Researcher 1	True	True	-	20:11:12	6	20:20
	Researcher 2	True	True	-	20:11:12	3	
	Final Decision	True	True	-	20:11:12	3	
5	Researcher 1	True	False	Non-Wear	-	-	02:05
	Researcher 2	True	False	Non-Wear	-	-	
	Final Decision	True	False	Non-Wear	-	-	

Table 6.6: Cont.

Fall ID	Round	Valid	Identified	Unidentified Reason	Identified ◷	Confidence	Reported ◷
6	Researcher 1	True	True	-	08:37:07	5	08:45
	Researcher 2	True	False	No Signal Matches Description	-	-	
	Final Decision	True	True	-	08:31:03	6	
7	Researcher 1	True	False	Non-Wear	-	-	20:30
	Researcher 2	True	False	Non-Wear	-	-	
	Final Decision	True	False	Non-Wear	-	-	
8	Researcher 1	True	False	Non-Wear	-	-	10:00
	Researcher 2	True	False	Non-Wear	-	-	
	Final Decision	True	False	Non-Wear	-	-	
9	Researcher 1	True	False	Non-Wear	-	-	06:10
	Researcher 2	True	False	Non-Wear	-	-	
	Final Decision	True	False	Non-Wear	-	-	
10	Researcher 1	True	True	-	06:42:23	3	06:50
	Researcher 2	True	True	-	06:41:16	8	
	Final Decision	True	True	-	06:42:23	7	

Table 6.6: Cont.

Fall ID	**Round**	**Valid**	**Identified**	**Unidentified Reason**	**Identified 🕒**	**Confidence**	**Reported 🕒**
11	Researcher 1	True	True	-	22:51:40	8	23:00
	Researcher 2	True	True	-	22:51:40	5	
	Final Decision	True	True	-	22:51:40	8	
12	Researcher 1	True	True	-	21:53:53	8	22:00
	Researcher 2	True	True	-	22:06:32	8	
	Final Decision	True	True	-	21:53:53	6	
13	Researcher 1	True	True	-	20:17:58	5	21:00
	Researcher 2	True	False	No Signal Matches Description	-	-	
	Final Decision	True	True	-	20:17:58	10	
14	Researcher 1	True	True	-	16:46:06	3	16:54
	Researcher 2	True	True	-	16:56:55	5	
	Final Decision	True	True	-	16:56:55	4	
15	Researcher 1	True	False	No Signal Matches Description	-	-	16:50
	Researcher 2	True	False	No Signal Matches Description	-	-	
	Final Decision	True	False	No Signal Matches Description	-	-	

Table 6.6: Cont.

Fall ID	**Round**	**Valid**	**Identified**	**Unidentified Reason**	**Identified 🕒**	**Confidence**	**Reported 🕒**
	Researcher 1	True	True	-	18:59:46	7	
16	Researcher 2	True	False	No Signal Matches Description	-	-	18:45
	Final Decision	True	False	No Signal Matches Description	-	-	
	Researcher 1	True	True	-	13:38:43	7	
17	Researcher 2	True	True	-	13:38:43	7	13:40
	Final Decision	True	True	-	13:38:43	7	
	Researcher 1	True	True	-	06:17:43	8	
18	Researcher 2	True	True	-	06:17:43	6	06:20
	Final Decision	True	True	-	06:17:43	10	
	Researcher 1	True	True	-	20:46:50	8	
19	Researcher 2	True	True	-	20:46:51	10	20:50
	Final Decision	True	True	-	20:46:51	10	
	Researcher 1	False	-	-	-	-	
20	Researcher 2	False	-	-	-	-	12:45
	Final Decision	False	-	-	-	-	

Table 6.6: Cont.

Fall ID	Round	Valid	Identified	Unidentified Reason	Identified ◷	Confidence	Reported ◷
	Researcher 1	False	-	-	-	-	
21	Researcher 2	False	-	-	-	-	23:30
	Final Decision	False	-	-	-	-	
	Researcher 1	False	-	-	-	-	
22	Researcher 2	False	-	-	-	-	21:45
	Final Decision	False	-	-	-	-	
	Researcher 1	True	True	-	03:14:17	6	
23	Researcher 2	True	True	-	03:14:01	8	03:30
	Final Decision	True	True	-	03:14:17	7	
	Researcher 1	True	True	-	10:41:54	7	
24	Researcher 2	True	True	-	10:41:53	9	11:15
	Final Decision	True	True	-	10:41:54	10	
	Researcher 1	True	False	Non-Wear	-	-	
25	Researcher 2	True	True	-	14:12:00	2	14:40
	Final Decision	True	False	Non-Wear	-	-	

Table 6.6: Cont.

Fall ID	Round	Valid	Identified	Unidentified Reason	Identified ◷	Confidence	Reported ◷
	Researcher 1	True	True	-	16:38:37	9	
26	Researcher 2	True	True	-	16:43:41	4	16:45
	Final Decision	True	True	-	16:38:37	10	
	Researcher 1	True	False	Non-Wear	-	-	
27	Researcher 2	True	False	No Signal Matches Description	-	-	07:30
	Final Decision	True	False	Non-Wear	-	-	
	Researcher 1	True	True	-	12:36:50	8	
28	Researcher 2	True	True	-	12:36:50	8	12:40
	Final Decision	True	True	-	12:36:50	8	
	Researcher 1	True	True	-	15:02:16	5	
29	Researcher 2	True	True	-	15:02:12	9	15:00
	Final Decision	True	True	-	15:02:16	9	
	Researcher 1	True	True	-	10:12:38	5	
30	Researcher 2	True	True	-	10:12:38	3	10:15
	Final Decision	True	True	-	10:12:38	8	

Table 6.6: Cont.

Fall ID	**Round**	**Valid**	**Identified**	**Unidentified Reason**	**Identified ◷**	**Confidence**	**Reported ◷**
31	Researcher 1	True	True	-	22:30:49	3	22:30
	Researcher 2	True	True	-	22:30:49	10	
	Final Decision	True	True	-	22:30:49	10	
32	Researcher 1	True	True	-	14:48:15	6	14:52
	Researcher 2	True	True	-	14:48:15	6	
	Final Decision	True	True	-	14:48:15	6	

Note: For Fall ID 3 the fall time identified by researcher 1 and in the consensus meeting are the day before the reported time.

Table 6.7: Details of the reported falls which were deemed invalid.

Fall ID	**Faller**	**Location**	**Fall Type**	**Severity**	**Description**	**Reported** ◷
2	2	Bedroom	From Standing	No harm	Resident was being supported to transfer from chair to chair. During the transfer the resident started to sit down when the chair wasn't close. The resident was slowly assisted to the ground.	10:25
20	14	Bedroom	From Standing	No harm	Resident was being encouraged to mobilise to bedroom doorway when they felt their legs giving way and was assisted to the floor by care staff.	12:45
21	14	Bedroom	From Standing	No harm	Resident lost their balance, while staff assisting them to the toilet. Staff assisted the resident to sit on the floor.	23:30
22	14	Bedroom	From Standing	No harm	Resident was being assisted by two members of staff with transfer. Resident's legs gave way when transfering and had a controlled descent to the floor, no impact taken.	21:45

Table 6.8: Details extracted from the fall reports for the falls identified in the accelerometer signals.

ID	Faller	Location	Fall Type	Severity	Description	Reported ◷	Identified ◷	Confidence
1	1	Corridor	Found on Floor	Minor harm	Resident had unwitnessed fall in main foyer, heard to be shouting for help by staff who immediately attended. Resident checked over physically and graze / bruise noted to top of head.	07:00	07:19:19	8
3	3	Bedroom	Found on Floor	No harm	Resident was found on the floor half sitting leaning against the wall on their right side in their bedroom toilet. Conscious and alert with no injury noted at the time.	01:30	22:10:28 (previous day)	6
4	4	Bedroom	From Standing	No harm	Unwitnessed fall, sensor mat alerted staff. Resident was found sitting on their bedroom floor beside the toilet door, they said they tripped on way to the toilet.	20:20	20:11:11	3
6	6	Day Room	Found on Floor	No harm	Resident was found on the floor in the lounge. No falls details known.	08:45	08:31:03	6

Table 6.8: Cont.

ID	Faller	Location	Fall Type	Severity	Description	Reported ◷	Identified ◷	Confidence
10	8	Bedroom	From Standing	Minor harm	Found on the floor by staff after their alert mat went off. Resident appeared more confused than usual due to chest infection. Abrasion on arm noted.	06:50	06:42:23	7
11	8	Bedroom	From Standing	No harm	Found on the floor in their bedroom. Residents's alert mat had alerted staff to attend, but on arrival resident was already on the floor. Resident was trying to get something out of their drawer.	23:00	22:51:40	8
12	8	Dining Room	From Standing	No harm	Resident got up from the chair they were sitting in, lost their balance and fell.	22:00	21:53:53	6
13	8	Dining Room	From Standing	No harm	As staff were supervising resident to sit in the chair they over balanced, resulting in them sliding to the floor.	21:00	20:17:58	10
14	9	Bedroom	Found on Floor	No harm	Resident was cleaning up a spill from their floor and tipped onto their bottom.	16:54	16:56:55	4

Table 6.8: Cont.

ID	Faller	Location	Fall Type	Severity	Description	Reported ◷	Identified ◷	Confidence
17	12	Corridor	From Standing	No harm	Resident was mobilising with wheeled zimmer frame, with wheelchair behind. As they were passing their bedroom door they realised that they were going to pass their room, panicked and dropped to their knees.	13:40	13:38:43	7
18	12	Bedroom	From Standing	No harm	Resident was found sitting on the floor. They were trying to use the commode unaided and unsupervised. They told staff that they lost balance while trying to get into bed, after using the commode.	06:20	06:17:43	10
19	14	Bedroom	From Standing	No harm	Resident was lying on the floor near their bed. They said they lost their balance, while trying to reach the wardrobe.	20:50	20:46:51	10

Table 6.8: Cont.

ID	Faller	Location	Fall Type	Severity	Description	Reported ◷	Identified ◷	Confidence
23	15	Bedroom	Found on Floor	No harm	Resident was found lying on the floor by staff. Staff reported that the resident was in bed when they did the routine night check about 10 min before. Resident didn't know how they ended up on the floor. They were not sure whether they hit head or not.	03:30	03:14:17	7
24	16	Bathroom	From Standing	Minor harm	Resident found on the floor in the bathroom after calling for help.	11:15	10:41:54	10
26	17	Corridor	From Standing	No harm	Resident was walking for their tea, misjudged their footing and fell to the ground. Staff and another resident witnessed fall.	16:45	16:38:37	10
28	21	Bedroom	Found on Floor	No harm	Resident was found on their bedroom floor.	12:40	12:36:50	8
29	22	Day Room	Found on Floor	No harm	Resident had an unwitnessed fall whilst in the conservatory.	15:00	15:02:16	9

Table 6.8: Cont.

ID	Faller	Location	Fall Type	Severity	Description	Reported ◷	Identified ◷	Confidence
31	23	Bathroom	From Chair	Minor harm	Resident buzzed as they had lost their balance trying to get on to the toilet. Abrasion on back noted.	22:30	22:30:49	10
30	23	Bathroom	Found on Floor	No harm	Resident was found on their bathroom floor 10:15, Resident stated they had fallen while trying to get from their wheelchair onto the toilet.	10:15	10:12:38	8
32	23	Bedroom	From Standing	No harm	Resident was found sitting on their bedroom floor, they stated that as they went to stand their left leg gave way.	14:52	14:48:15	6

Note: The identified time and confidence refer to the identified signal following the consensus meeting.

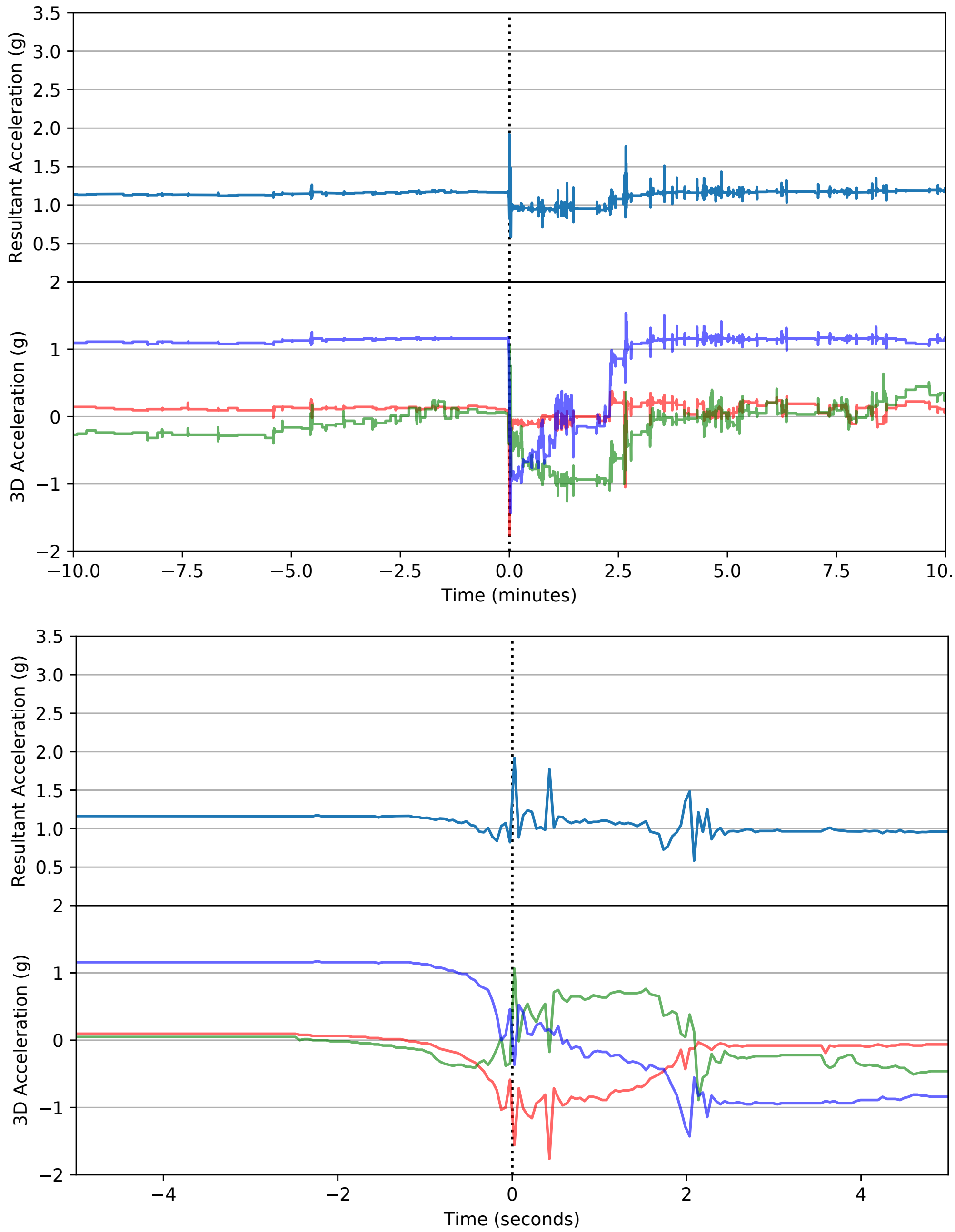


Figure 6.4: Example fall signal A. The point identified as the fall is marked with a dotted line. For the 3D acceleration red=X, green=Y and blue=Z activPAL axes. The top plot shows the 20 minutes around the fall, the bottom plot shows the 10 seconds around the fall. Fall description: Resident had unwitnessed fall in the main foyer, heard to be shouting for help by staff who immediately attended.

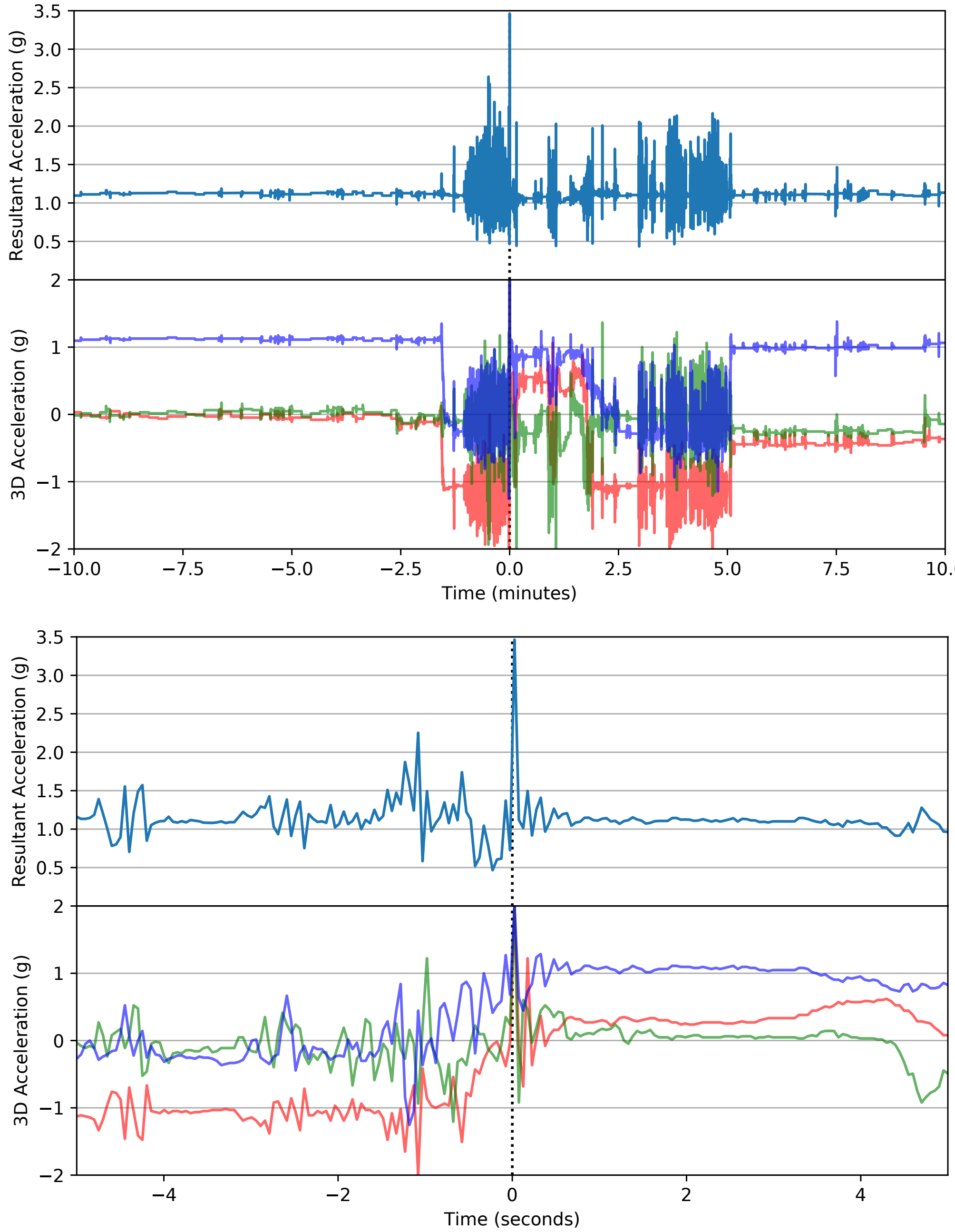


Figure 6.5: Example fall signal B. The point identified as the fall is marked with a dotted line. For the 3D acceleration red=X, green=Y and blue=Z activPAL axes. The top plot shows the 20 minutes around the fall, the bottom plot shows the 10 seconds around the fall. Fall description: Resident was walking for their tea, misjudged their footing and fell to the ground.

6.5 Discussion

6.5.1 Collection of a Real-World Fall Dataset

In collaboration with Four Seasons Health Care, a project was conducted to collect real-world fall data which could be used to research new approaches to fall detection. As a result of this collaborative project, a dataset of 1,919 days of recording was collected from which twenty falls were extracted. The original objective to recruit 250 participants and record 100 falls was not achieved, however, the collected dataset of twenty falls and 1,919 days of recordings is one of the largest real-world fall datasets which has been collected. The median number of falls used in previous studies was 17.5 (IQR 8.25 to 29 falls) and the median total length of recorded data was 592 days (IQR 21 to 1474 days) (Section 4.3.3). Only four datasets containing substantially more falls have been collected (see Table 4.2); the highest number of falls used in published studies is 218 recorded with a Kinect™ sensor [143] and 100 recorded with an accelerometer [122].

The size of the dataset was limited by fewer participants than anticipated and a higher rate of participant withdrawal, rather than a low occurrence of falls. The care homes reported that the majority of potential participants had some form of cognitive impairment and that gaining assent for those who lacked mental capacity was challenging. The need to contact relatives (for consultation on participation) was the primary challenge, relatives were most commonly working age and not necessarily local. This meant visits were often infrequent and outside of normal working hours which made contact challenging and heavily restricted the opportunity to provide information about the study and to go through the recruitment pathway. The care homes reported that there was often a reluctance to provide consent or assent as those being asked did not see how the research would benefit those involved. Given this feedback, people may be more willing to participate in studies where a functioning (prototype) alarm is used; this was not possible at such an early stage of development.

Given the duration of the study, it was not expected that all participants would complete the study and wear the device for the full two months. However, the withdrawal rate was higher than anticipated; only fifteen participants completed the two months of data collection. Fifty percent of participants wore the device for less than one month and twenty-five percent for less than two and a half weeks. Twenty percent did not complete as they were discharged from the home or deceased; future studies should account for this when planning participant numbers. Twenty-four percent did not complete because they did not want to wear the monitor or lost multiple monitors, highlighting the challenges in recording data with a wearable device over extended periods. Further, these findings suggest a fall detector worn in a similar way to the device used in this study may not be acceptable to users; additional research is needed before an investment is made in a thigh-worn fall alarm sensor.

Falls were captured during the current study at a very similar rate to that predicted based on previous studies. Previous studies had recorded falls at a rate of approximately 100 to 1,000 days per fall depending on the fall risk of participants. Given that those with a history of falls were recruited for the current study, one would expect the fall rate to be at the lower end of this range. In this study, falls were captured at a mean rate of 96 days per fall, in line with previous studies.

Given the high rates of withdrawal, an increase in the duration of data collection for each participant would have been unlikely to result in substantially more data or falls being recorded, as few participants would have continued to wear the activPAL device. If the target of 250 participants had been reached then, all else being equal, around 100 falls would have been recorded. Therefore, the lower than anticipated participant recruitment was the primary factor which limited the size of the dataset.

Participants were recruited from seventeen care homes and around fifty people were directly involved in participant recruitment, none of which had prior experience supporting research such as this. In addition, the care home company had many layers of management between the senior managers who were the partners on the project and the care staff who recruited participants. Consequently, it was difficult to ensure all those involved in the recruitment of participants understood the value of the project and were able to convey the benefits of the research to potential participants. The priority of the care homes was delivering quality care to their residents and this project was an extra responsibility with no funding for staff time provided. As a result, only a limited amount of time could be spent on participant recruitment and this is likely the main factor which limited participation. Future studies where recruitment is carried out by a partner organisation should carefully consider the level of support needed to ensure recruitment targets are met.

There were also challenges in ensuring that all processes during the data collection were followed. The requirements were kept to a minimum of checking the device attachment regularly, recording when it was worn, monitoring participant comfort and ensuring their normal fall reports were accurate. However, the record of when the device was worn was not always completed and around twenty activPAL devices were lost during the project. This could be explained by challenges in providing training to all those who provided care for participants and the high workload of those staff.

Over 250 staff across seventeen care homes were directly involved in providing care to residents who participated and given staff turnover and varied shift patterns it was not possible to provide all staff with face-to-face training. Visits were made to each home before data collection began and senior staff were all given training and instructed to disseminate the information to their staff; written documentation was provided to assist with this process. Similar to participant recruitment, the data collection was not the priority of care staff, and given their high workload it is perhaps unsurprising that some record-keeping was overlooked. Future studies should ensure they have the resources to either make frequent visits to each site and provide support or have a researcher working on-site to oversee the recruitment and data collection.

6.5.2 Fall Signal Identification

The accurate identification of the fall events in the recorded accelerometer signals was a critical first step in preparing the dataset for analysis. Many previous studies have not published details of how they identified the fall signals (for a review see Section 4.3.4). Only the FARSEEING consortium have published an approach to fall signal identification and their approach was used here. To maximise the robustness of the fall signal identification process two researchers independently analysed the signals and identified the falls based on the fall reports received from the care homes. Where the researchers agreed it gives confidence in the result, where they disagree it highlights that there is uncertainty as to when the fall occurred.

There was a good level of agreement in the identified fall signals; half of the falls could be identified independently to within one second. In each of these cases, the same movement was identified as the fall, even if a different sample was marked as the point of impact. For the other ten falls, the consensus meeting provided a forum to re-analyse and discuss the signals until a unanimous decision could be reached, increasing the likelihood of identifying the correct point in the signals for the more challenging falls.

As a reflection of the fact that one cannot be certain the correct signal had been identified the confidence that the correct signal had been identified was recorded. Following the consensus meeting, the scores for confidence in the signals which had been identified as the falls were high (mean 7.65 ± 2.08). There was no correlation between the confidence in the marked point and agreement, in fact for the fall with the lowest confidence both researchers marked the same sample. The robust method used maximised the likelihood that the correct signals were labelled as falls, while the independent agreement on half of the falls and high confidence scores following the consensus meeting provide further trust in the results. The method used here is based on the FARSEEING approach which was devised by experts in the field and is the most robust method which has been used for fall signal identification.

6.5.3 Challenges in the Analysis of Real-World Fall Data

Due to only being able to extract twenty falls the analysis which can be carried out is limited. There is not enough data for a study of the fall signals and then a test of a new algorithm developed based on the findings. A test of an algorithm requires data which is independent from that used to develop the algorithm, splitting the twenty falls between these two applications would be counterproductive; there are not enough fall samples to train a robust classifier and properly evaluate performance. Twenty examples may not be enough to fully characterise falls, given that they are highly variable. However, given that previous analysis of real fall signals has been limited, even analysis of twenty examples provides a valuable contribution to the field. Further data collection will be needed to check if any findings generalise and to test any new fall detection technology based on said findings.

The limited size of the dataset is not the only factor which must be considered in the analysis. Due to the study being observational and over an extended period, very little is known about the movements recorded and this makes it difficult to assess the quality of the data. For one fall it was identified that the device was worn upside-down only because of a period of walking before the fall where the X-axis was inverted. However, generally it is hard to verify that the device was worn correctly, the period around the fall was only spotted because the fall signals were carefully examined. Walking is generally the only activity which is recognisable even if the device is not orientated correctly; the cyclic pattern of steps and spikes due to impact are both recognisable and unique. Finally, to check device orientation based on periods of walking requires a fine-grained examination of the data at a level where individual steps are distinguishable, to do this for almost 2,000 days of data is extremely onerous.

Similar to checks of orientation, checking for periods where the device was not worn is a challenging task. Due to participants sometimes removing the device themselves the wear-time reports received from the care homes were incomplete and the accuracy of the times cannot be relied upon. Therefore, these reports can only be used as a guide, manual analysis of the recorded signals is required to increase the accuracy in the extraction of periods where the device was worn. As with checking device orientation, examining the data to check for periods of non-wear is onerous. Where the device is not worn for an hour or more, this can be identified relatively easily due to the complete lack of movement However, identification of when the device was removed from the thigh and when it was reattached is complicated by movement when the device is not worn. The device is rarely set down as soon as it is removed, staff may carry the device in their pocket, for example.

There are several potential issues which must be considered when working with these real-world fall data. Due to the length of the study and its observational nature, it was not possible to fully track when the device was worn and if it was worn correctly. It is possible to improve the accuracy of wear-time records and identify some periods where the device was not orientated correctly, however, due to the volume of data this process is extremely onerous. It is not uncommon for only a subset of the data to be analysed [e.g. 149] and this is something which needs to be considered for the analysis of this dataset. While reducing the volume of non-fall data included is not ideal, it will allow the quality of the data to be checked and any necessary corrections or exclusions to be applied, thereby increasing the reliability of the findings.

6.5.4 Conclusion

This project aimed to collect a real-world dataset of falls and activities of daily living comparable in size to the largest used in previous studies. Real-world movement data totalling 1,919 days were collected across seventeen care homes over two years and twenty fall signals were extracted. There was a good level of agreement in which signals corresponded to the falls and the confidence that the correct signal was identified was generally high. This is one of the larger real-world fall datasets to have been collected and represents a significant contribution to the field. There are several challenges to overcome in analysing the collected data; this is the nature of a real-world study where control is limited. However, there is huge value in the analysis of the fall signals and comparison to other movements and such analysis must be carried out to identify how wearable fall detection technology can be improved.

Chapter 7

Analysis of Real-World Fall Signals Recorded With a Thigh-Worn Accelerometer

7.1 Introduction

Through a review of the literature (Chapter 3), it was identified that there is a need for research into how falls differ from other movements to produce a base of evidence on which improved fall detection technology can be designed. In Section 3.7, a new framework for the development of fall detection technology was proposed. Previously, testing the performance of fall detection technology had been the focus of the research, in the new framework this plays a relatively small part. Instead, the framework emphasises research to build an evidence base and inform future design iterations, something which has been lacking in the literature. This study aimed to use the collected real-world dataset (Chapter 6) to address this gap in knowledge and to begin the work of developing new fall detection technology in line with the proposed framework.

7.1.1 Background

Current fall detection technology has not performed adequately on real-world data (Section 3.6) and it is not clear how performance can be improved. Early in the development of fall detection technology, efforts were made to define a fall (Section 2.1.1) and to propose a fixed sequence of phases which make up a fall (Section 3.1). However, while this put some structure on the problem area it did not properly address the wide variety of ways people fall and hence offered little in terms of the ability to discriminate real falls from other activities.

A series of studies to compare features of simulated falls to activities of daily living (ADL) carried out in a laboratory environment were conducted over a decade ago [107,113,119]. In these studies, data were recorded with wearable sensors as young, healthy adults performed a series of falls and older adults performed a scripted set of ADL (e.g. sitting on and standing from a chair, walking, getting into and out of bed, etc.). Between them, these studies analysed the magnitude of impact, peak vertical acceleration and peak torso angular velocity (further details of these features can be found in Section 3.5.2). The results showed that for falls the values were typically higher compared to other activities, although an overlap between the falls and ADL was found. This work has been highly influential within the field, with a total of over 1,500 citations between the three articles (according to Google Scholar in October 2019), and has formed the basis for the wearable fall detection approaches which have since been proposed.

There is a growing body of evidence that simulated falls are not the same as real-world falls and because of this, approaches to fall detection which perform well in the laboratory generally perform poorly in the real-world (Section 3.4). In light of this, it is important to conduct studies to compare real-world falls and ADL to provide a more accurate understanding of how falls differ from other movements. Only one study has been published which has analysed real-world data to identify features of falls which make them unique [114]. Consequently, there is little understanding of why fall detection technology has performed poorly in the real world or how it can be improved. Further studies to compare features of real-world falls and ADL should, therefore, be prioritised over the testing of prototype fall detection technology.

Bourke et al. [114] used data collected as part of the European Union funded FARSEEING project. The project's data were collected over a period of four years by six institutions, who between them recorded activity data from over 2,000 participants. Bourke et al. [114] extracted and compared three temporal and three kinematic features of 100 falls and 1,908 ADL recorded with a lumbar-worn triaxial accelerometer. ADL were extracted from an undisclosed volume of data using a previously developed motion detection algorithm [180] and a threshold for the peak in the resultant acceleration of greater than 1.05 g. From the signals Bourke et al. [114] extracted the following kinematic features: (1) maximum resultant acceleration (impact magnitude), (2) minimum resultant acceleration and (3) the maximum torso angle. The temporal features extracted from the signals were: (1) the time between the minimum and maximum resultant acceleration (lead-time), (2) the time relative to the point of peak resultant acceleration at which the peak torso angle occurred and (3) the time relative to the peak resultant acceleration when lying began, based on a torso angle threshold.

Through the use of T-tests, and Mann–Whitney U tests where data were not normally distributed, Bourke et al. [114] reported significant differences ($p < 0.001$) between the falls and ADL for the maximum resultant acceleration, the minimum resultant acceleration and the maximum torso angle. However, plots of the data (boxplots and histograms, see Figure 7.1 for an example) revealed substantial overlap between the falls and ADL groups for all features. Bourke et al. [114] did not quantify the overlap between groups, however, as can be seen in Figure 7.1 there are a substantial number of ADL with maximum and minimum resultant accelerations within the range observed for the falls. The overlap for other features analysed by Bourke et al. [114] was similar to those shown in Figure 7.1; see the original article for full results.

For some classification problems, a combination of features with overlapping distributions such as those found by Bourke et al. [114] may yield acceptable results with an optimised classifier. However, fall detection is an extreme case due to the relative rarity of falls and the potential consequences of false negatives (failure to detect a fall). Fall detection requires both high sensitivity and precision to ensure that the system can be relied upon to detect falls, without inducing alarm-fatigue. Since falls are rare, correct detections are rare and so even a small proportion of ADL events being mistaken for a fall would lead to substantially more erroneous detections than correct ones. If the frequency of errors significantly exceeds the frequency of correctly detected falls, trust in the system could be eroded which may contribute to alarm-fatigue.

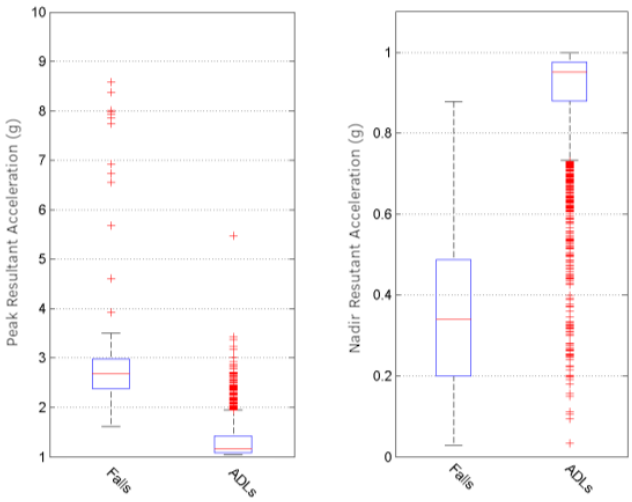


Figure 7.1: Example of the overlap between falls and ADL observed in previous studies (adapted from Bourke et al. [114]).

There is a need to explore new features, as those which have been used previously have not yielded acceptable fall detection performance. Differences in peak jerk (rate of change in acceleration) have been found between real and simulated falls [15], however, the use of peak jerk to detect falls has not been tested. Another area which could be explored is the number of impacts, there is no evidence that falls have a single large impact, although previous approaches to wearable fall detection appear to have been based on this assumption. If falls are found to commonly have multiple impacts and this is not the case for other movements, then further analysis of these impacts could be useful for fall detection and would, therefore, warrant further investigation.

In addition to analysis of features which have not been used previously, it is also important to study features which have been common, but were not included by Bourke et al. [114], namely vertical velocity, to understand if it is useful in fall detection or superfluous. Another area which has yet to be studied is the interaction between features. It is currently unknown whether the combination of impact magnitude and vertical velocity, for example, allows greater distinction between falls and other movements, compared to either feature individually. Since classification typically requires multiple features, understanding how they interact is important to guide the selection of features and avoid increasing complexity unnecessarily with features which add little or no value.

It may be that falls are too diverse to be categorised as a single group for classification. Instead, it may be better to divide falls into subcategories and develop separate classifiers for each subgroup. One method to divide falls is based on the type of posture transition, for example, standing to sedentary or walking to sedentary. This approach could potentially allow greater distinction between falls and other movements but since no research has been conducted on this, the benefit remains unknown. Identification of transition type could also allow features specific to each type to be extracted. As an example, features associated with steps could be extracted for a transition from walking, but the same approaches may give unpredictable results for falls from quiet standing.

To divide the falls into subgroups would require a large dataset so that each group contained sufficient data for robust analysis. As part of the research for this thesis, a dataset of twenty falls were collected from care homes in the UK. This was not considered a sufficiently large sample for division into multiple subgroups. Preliminary analysis, in the form of visual inspection of the signals, revealed that sixteen of the falls were transitions from an upright to a sedentary (sitting or lying) posture. Therefore, the focus of this study was to explore the characteristics of upright to sedentary falls and posture transitions.

7.1.2 Aims and Objectives

This study aimed to analyse features of both falls and normal upright to sedentary transitions to identify which features are suitable for fall detection. In addition, this study aimed to analyse interactions between features for the first time and provide an understanding of which combinations provide the greatest separation between falls and normal transitions. A final objective in conducting this analysis was to enhance the understanding of why existing fall detection technology has not achieved an acceptable level of performance.

7.2 Data Pre-Processing

Pre-processing of the data was carried out to ensure that the data included in the study were only from periods where the device was worn and that any periods where the device was worn incorrectly were corrected or removed if a correction was not possible. As noted in Section 6.5.3, to carry out such work for the entire dataset (1,919 days of recordings) would present a significant burden. Therefore, to allow the data to be checked and periods of wear identified, only the recordings which contained falls from upright to sitting or lying were included in the current study (as identified by an upright to sedentary detection algorithm, see Section 7.3). There were fifteen recordings which contained such falls and were included in the study; the total length of these recordings was 138.8 days and they contained sixteen falls.

For each included recording the signals were visually inspected to identify and mark periods where the device was worn and also to note where the device was not correctly orientated on the thigh. The device wear times reported by the care homes were used to guide the visual inspection. For each point which marked either the start or end of a period of wear, the confidence that the selected time was correct was recorded subjectively using a ten-point scale. Where the precise time for the start of a period of wear could not be identified, the first point at which the researcher was confident the device was worn was recorded, similarly, for the end of a period of wear, the last point where there was confidence the device was worn was recorded. Thus, the chance of periods of non-wear being included in the analysis was minimised, but some valid data near the start or end of a period of wear may have been excluded.

Where inspection of the signals suggested that the device had been worn rotated by 180° about one of its axes, this was corrected by inverting the signals for the other two axes; for example, if upside-down (rotated 180° about the Z-axis) the values for the X and Y-axes were inverted to correct the orientation. It was not possible to identify and correct small errors in orientation, to do so would have required some form of calibration each time the device was attached to participants' thighs. Such calibration was not carried out during the data collection as no method could be identified which was suitable; any method would need to have been quick and easy to perform, required only simple equipment and been suitable for all levels of mobility. Therefore, the set of features which were extracted from the data (Section 7.4) were designed to be robust to small differences in device orientation.

To carry out the visual inspection of the signals, a software application (the raw_marker module) contained in the uos_activpal python package [181] was used. The uos_activpal package contains the core elements of software developed for the research in this thesis and provides a base for custom data processing software. The raw_marker module used here was the basis on which the fall signal identification application (Appendix F) was built, it appeared and functioned in the same way, the only difference being that it was generic and not tailored to fall identification. The software allowed: (1) activPAL data files to be selected, loaded and plotted, (2) a marker to be placed and (3) information about the marker (file name, sample number, date and time, what was marked and a comment) to be added to a CSV file. The resulting data were added to a new "wear" table in the database which stored all the metadata for the real-world dataset (details of this database are given in Section 6.3.1). The wear table contained all details of the start and end of each period of wear as well as any transformations needed to correct for issues with the orientation of the device on the thigh. Each period of wear was loaded and any orientation corrections were applied prior to analysis.

7.3 Event Selection

The focus of this study was falls from upright to sedentary postures and how they differ from normal (non-fall) upright to sedentary posture transitions. Therefore, only transitions from upright to sedentary were of interest and only these events were selected for analysis. An algorithm to classify upright and sedentary postures was developed and tested previously (see Section 5.3 and Section 5.7.2 for the design and performance respectively). The gravitational component of the signal for the X-axis was estimated using a one-second moving-average filter and a state-based algorithm with two thresholds was used for classification; $X < -0.81$ g for the state to become upright and $X > -0.52$ g for the state to become sedentary. This algorithm formed the basis of the event selection used in the current study.

The thresholds for the previous algorithm were set based on data collected in the laboratory of young adults standing, sitting and lying. The data only covered young adults standing fully upright, and so (1) the algorithm was not optimised for older adults, and (2) the algorithm may not detect a valid upright posture if a fall occurred during standing up from a sedentary position. For the current study perfect classification was not the focus, instead, the objective was to simply identify that a transition from an upright (or near upright) posture to a sedentary one had occurred. Therefore, the thresholds were adjusted to reduce the upright threshold to -0.75 g and the sedentary threshold was rounded to -0.5 g, these correspond to forty-nine degrees and thirty degrees (rounded to the nearest degree) from horizontal respectively, as shown in Figure 7.2. These changes reduce the angle required to enter the upright state by five degrees while maintaining a buffer between the thresholds to prevent posture transitions being identified where there is fluctuation around a single point, as could occur with only a single threshold.

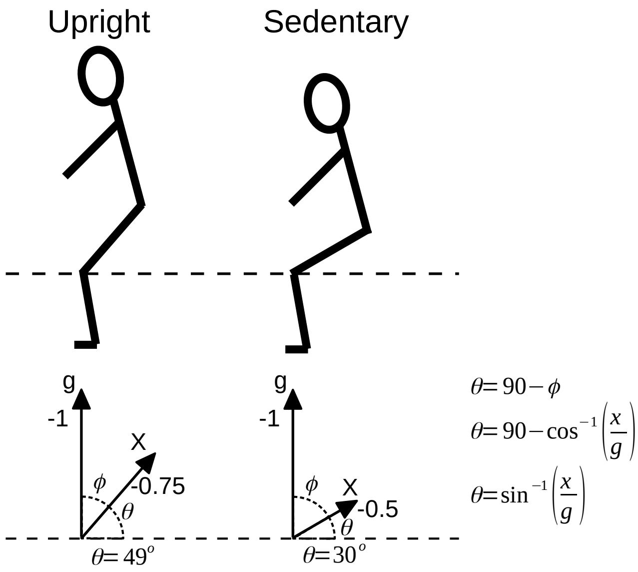


Figure 7.2: The thresholds for upright and sedentary postures. When X < -0.75 g the state becomes upright, when X > -0.5 g the state becomes sedentary. The stick figures show the thigh angles for transitions to or from a seated posture, a rotation of the thigh forward or tilt laterally would be equally valid.

The term "event" is used here to refer to the whole period of interest for the purpose of analysis, this includes the upright to sedentary transition and the first few seconds spent sedentary; in the case of a fall, this would be the fall and the first seconds spent on the floor. The start of each event was taken as 0.5 seconds before the upright threshold was crossed (X $\geq$ -0.75 g), an approximation of the start of the upright to sedentary posture transition. The end of each event was taken as either: (1) five seconds after the sedentary threshold was crossed (X $\geq$ -0.5 g), (2) the point where the state reverted to upright (X < -0.75 g) or (3) the end of the period of wear, whichever came first. Figure 7.3 shows the process of event extraction for an example fall signal. Events, where the time between crossing the upright threshold and the sedentary threshold was greater than thirty seconds, were excluded; this was done because such slow transitions would be highly unlikely to be a fall and so were of no interest. The database was queried for the details of the previously identified falls and the events were labelled accordingly.

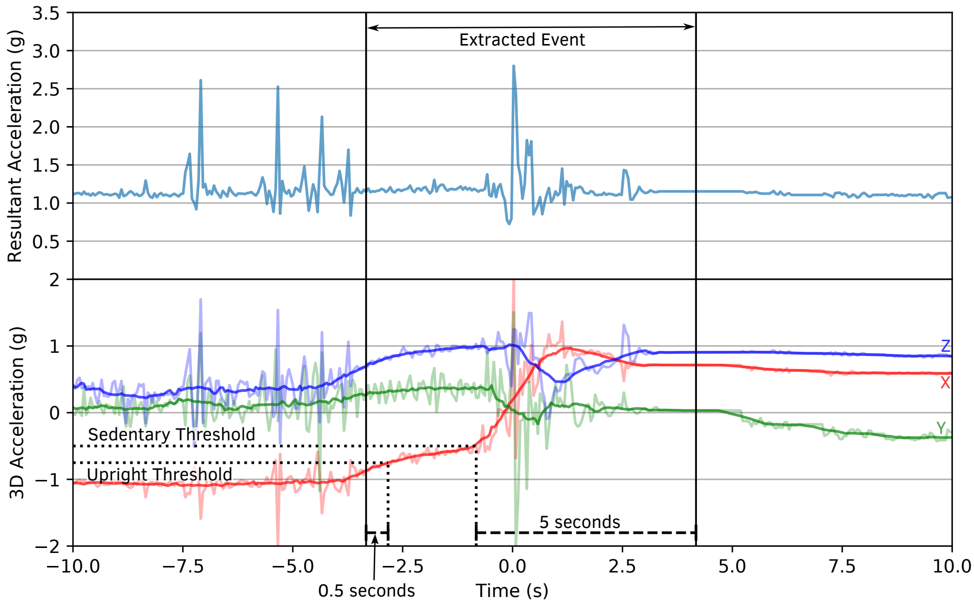


Figure 7.3: Example extraction of an upright to sedentary posture transition for a recorded fall signal. The start of the event was taken as 0.5 seconds before the upright threshold was crossed and the end of the event was taken as five seconds after the sedentary threshold was crossed. On the lower plot the darker lines are the moving average filtered data and the lighter lines are the raw accelerometer signal.

7.4 Feature Extraction

Kinematic and temporal variables (features) were extracted from the signals of each upright to sedentary transition, this section describes the methods used to extract these features from the accelerometer signals. The methods used in this study are based on those commonly used in previously developed fall detection algorithms, an overview of common features extracted from accelerometer signals can be found in Section 3.5.2.1. Custom written Python software was used to process and extract features from the signals with the SciPy package [182] used to provide key functions including: filters, interpolation, integration and peak identification.

As part of the feature extraction procedure, a series of signal processing steps were carried out to calculate the resultant acceleration and to isolate components of the acceleration signals. The resultant acceleration ($\boldsymbol{a}_r$) was calculated by taking the root-sum-of-squares of the signals from the three axes of the accelerometer (Equation 7.1). The resultant acceleration was high-pass filtered using a digital second-order Butterworth filter with a cutoff of 0.25 Hz to remove drift in the signal. The cutoff frequency was selected based on previous studies which had also used 0.25 Hz [e.g. 20,113]. For the orientation-based calculations, a one-second moving-average filter was used to estimate the gravitational component of the signals, as was done for the identification of upright to sedentary transitions.

$$\text{Resultant Acceleration } (\boldsymbol{a}_r) = \sqrt{\boldsymbol{a}_x{}^2 + \boldsymbol{a}_y{}^2 + \boldsymbol{a}_z{}^2} \tag{7.1}$$

7.4.1 Impact

Impact was characterised in four ways, (1) the peak deceleration (impact magnitude), (2) the time of the main impact peak relative to where the upright threshold was crossed, (3) a count of peaks in the acceleration signal, and (4) peak jerk (rate of change of acceleration). The magnitude of the impact was calculated as the height of the largest peak in the high-pass filtered resultant acceleration, as shown in Figure 7.4. As multiple impacts may occur during a fall, a count of the peaks with a height greater than 0.5 g was taken using the find peaks function provided by SciPy [182]. Since no previous fall detection studies had included a count of impacts, the threshold for peak height was arbitrarily chosen with the intention that only peaks which could potentially be a result of significant impact were included and not peaks due to general movement of the thigh. The counted peaks for an example fall signal are shown in Figure 7.4. To provide an estimate of the duration of the fall, the time between the upright threshold being crossed and the main impact peak was also recorded. To assess the prevalence of clipping, a count was taken of the number of axes which recorded a maximum value of ±2 g at the impact peak for each event.

For comparison between falls and other upright to sedentary transitions, the peak jerk between the time of the pre-impact nadir (the method used to identify this point is explained in Section 7.4.2) and the main impact peak was extracted. Jerk is the rate of change in acceleration and was therefore calculated by taking the gradient of the resultant acceleration signal. Since the impact peak is a result of high deceleration, the peak jerk immediately prior is the peak rate of deceleration. Jerk was calculated using Equation 7.2, where i refers to any sample in the window of interest.

$$\text{Jerk } (j) = \frac{\boldsymbol{a}_{r(i)} - \boldsymbol{a}_{r(i-1)}}{\Delta t} \tag{7.2}$$

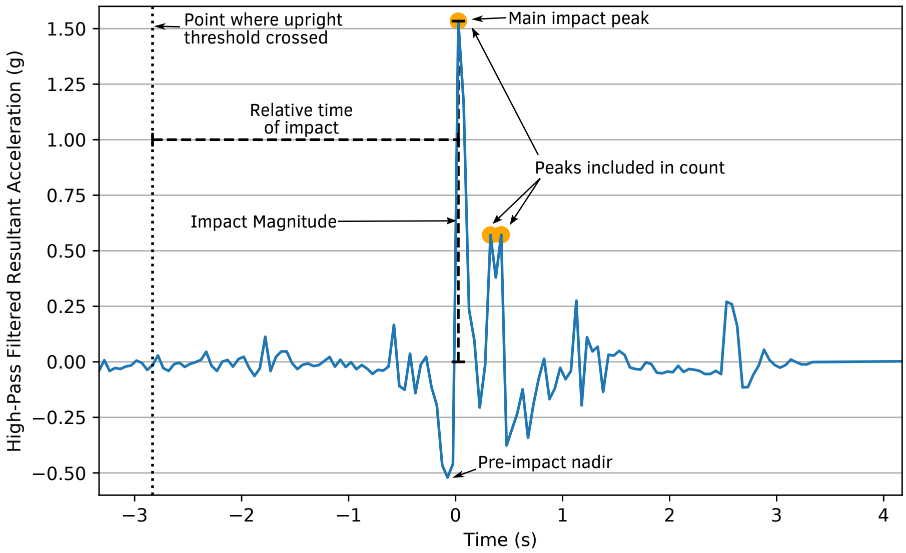


Figure 7.4: Example extraction of impact-related features for a recorded fall signal. The impact magnitude was taken as the highest peak with the period shown in the plot and the count of impacts was taken for the same period. The time of the main impact was taken relative to the point where the sedentary threshold was crossed. Peak jerk was calculated as the maximum gradient of the signal between the pre-impact nadir and the main impact peak.

Jerk has not been common in previous fall detection research, however, Klenk et al. [15] found differences in peak jerk between real and simulated falls. Previously the main impact peak has been characterised solely by the height, a feature which has been shown does not fully distinguish falls from other movements [114]. One would expect the peak due to deceleration upon impact to be relatively narrow, and therefore, the steepness of the slope may be more indicative of a fall, especially ones which do not have an exceptionally high peak. This approach may also be better where the range of the sensor is limited, as with the activPAL3 used in this study.

7.4.2 Vertical Motion

The period of vertical motion was characterised in two ways, (1) an estimation of peak vertical acceleration, and (2) an estimation of vertical velocity. Peak acceleration towards the ground was estimated as the nadir in the high-pass filtered resultant acceleration up to two seconds before the main impact peak, as shown in Figure 7.5. Where the main impact peak occurred within the two seconds of the event start, the event start was used as the start of the search window. This reduced the possibility that signals from any ambulation before the upright to sedentary transition would be erroneously included in the vertical motion analysis. In instances where the lowest acceleration in the search window was the first sample, the search for the nadir was extended backwards to find the turning point (local minima). To allow comparison to the results of Bourke et al. [114], the time between the pre-impact nadir and the impact peak (lead-time) was also extracted.

An estimate of vertical velocity at the point of impact was obtained through integration of the high-pass filtered resultant acceleration around the pre-impact nadir, where the signal was less than zero, as shown in Figure 7.5. To improve the accuracy of the velocity estimate, interpolation via a cubic spline was used to estimate the time points where the signal crossed zero which were used as the limits for the integration. Simpson's rule was used to perform the integration of the recorded signal and integration of the cubic spline was used between the first and last recorded negative values and the interpolated zero points, as shown in Figure 7.6. These values for the areas under each section of the curve were summed to produce the vertical velocity estimate.

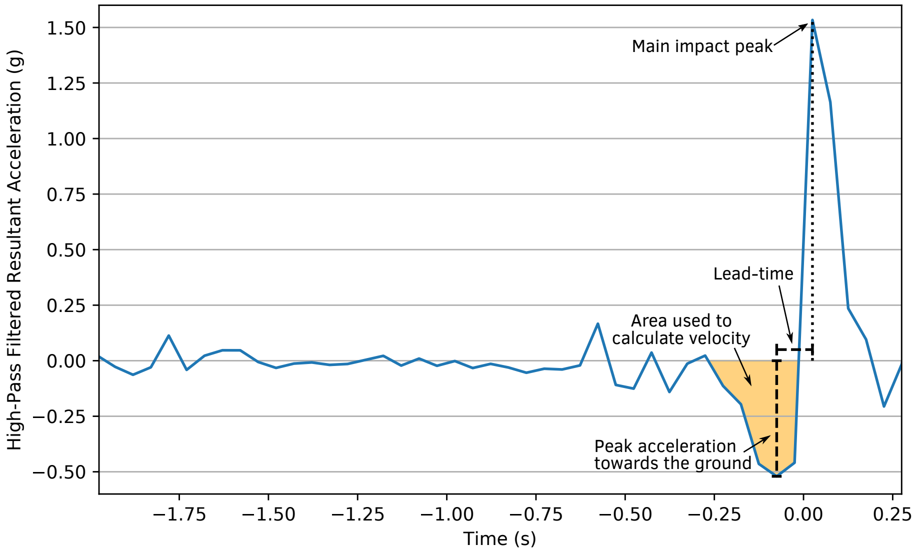


Figure 7.5: Example extraction of vertical motion related features for a recorded fall signal. The peak acceleration towards the ground was taken as the lowest point in the 2 seconds before the main impact. Vertical velocity was estimated as the area highlighted in orange. The lead-time was taken as the time between the pre-impact nadir and the main impact peak.

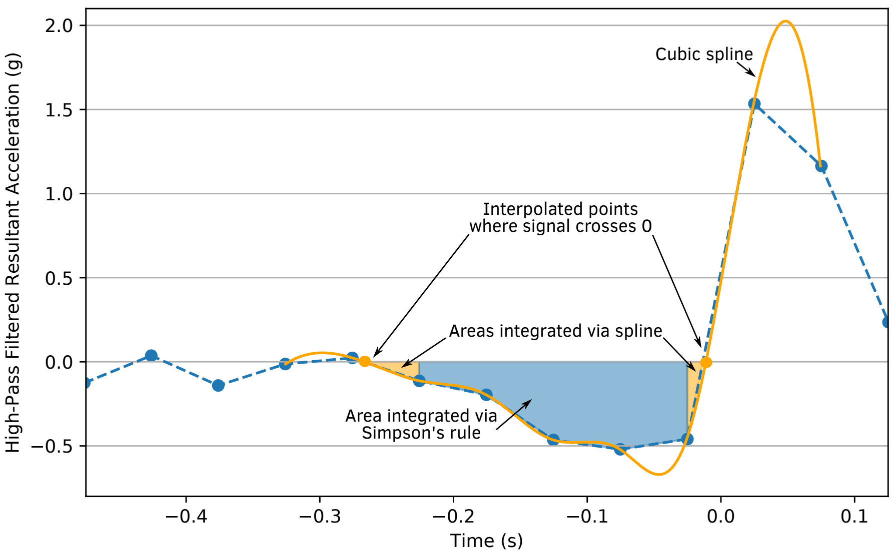


Figure 7.6: Example estimation of vertical velocity for a recorded fall signal. The integral of the recorded signal was estimated using Simpson's rule. A cubic spline was used to interpolate where the signal crossed zero and to estimate the integral of the signal between the recorded samples and the interpolated zero-crossing points.

7.4.3 Change in Orientation

The change in the direction of the resultant acceleration was calculated using Equation 7.3, where t1 was the point where the upright threshold was crossed in the transition to a sedentary posture and t2 was two seconds after the main impact peak. For the calculation of change in orientation all signals ($\boldsymbol{a}_x, \boldsymbol{a}_y, \boldsymbol{a}_z, \boldsymbol{a}_r$) were filtered using a one-second moving average to estimate the gravitational component of the signals.

$$\text{Orientation Change } (\theta) = \cos^{-1}\left(\frac{\boldsymbol{a}_{x(t1)} \cdot \boldsymbol{a}_{x(t2)} + \boldsymbol{a}_{y(t1)} \cdot \boldsymbol{a}_{y(t2)} + \boldsymbol{a}_{z(t1)} \cdot \boldsymbol{a}_{z(t2)}}{\boldsymbol{a}_{r(t1)} \cdot \boldsymbol{a}_{r(t2)}}\right) \quad (7.3)$$

7.5 Analysis of Features

To show the challenge in distinguishing between falls and normal upright to sedentary posture transitions, plots of each fall along with a similar normal transition were produced. The values for the eight extracted features were standardised as z-scores and similarity was calculated as the mean absolute difference in z-scores between each fall and the normal transitions. For each fall, the similarity scores were used to short-list the ten normal transitions with the lowest mean difference and then each short-listed transition was visually inspected to select the posture transition to plot.

Given the small sample size for the fall group (n=16) it was not possible to establish if the data were normally distributed [183], and therefore, the assumptions of parametric tests such as the T-test could not be tested. In addition, results from previous studies, both lab-based and real-world, indicate features such as impact magnitude are not normally distributed and that outliers are common [106,113,114]. Given this, the Mann-Whitney U test was chosen to test for significant differences between the falls and the normal upright to sedentary transitions. Due to the use of multiple tests (one for each feature) the probability of type I errors was increased; to correct for this, p-values were adjusted using a Bonferroni correction. The Bonferroni correction is a conservative method, however, given the small sample of falls, it was preferable to take a conservative approach and minimise the risk of type I errors.

The Mann-Whitney U test gives a U score which indicates the overlap between the groups. U has a maximum value of $n_1 \times n_2$ where n_1 and n_2 are the sample sizes for each group, to make the result easier to interpret the ρ statistic was calculated as $\rho = U \div (n_1 \times n_2)$. ρ is the probability that the value for one group will be larger than for the other group when comparing random samples from each group; a ρ of 0.5 indicates total overlap, a ρ of zero or one indicates total separation in opposite directions. U, and therefore ρ, are calculated for each group, and typically the smaller score is reported, however, in this study, the results for the fall group are reported to highlight whether the falls measured higher or lower than the normal transitions.

Violin plots were used to visualise the distributions for each group and feature. Violin plots are similar to, and based upon, box and whisker plots, but the width of the box is proportional to a density estimate; these plots, therefore, provide greater insight into the distribution of the data. An in-depth discussion of violin plots has been written by Hintze and Nelson [184]. To explore interactions between the features where significant differences between groups were found, scatter and density plots were produced showing one feature against another. Data visualisations were produced using the Python package seaborn [185].

To assess the correlations between features, Pearson's product-moment correlation coefficient was calculated for each pairing of features which individually were found to be significantly different for the two groups. The correlation coefficient was calculated separately for both the falls and the normal upright to sedentary transitions. Where both groups showed a strong correlation and the scatter plot indicated no clear difference in the direction, little or no information could be gained from the use of both features over just one of them. Where there was a difference in the correlation between groups, the separation between groups was likely greater with both features compared to either individually.

7.6 Results

Following the process of manually screening the data, a total of 34.8 days of data were identified as non-wear and were subsequently removed, leaving 104 days for analysis. Twenty-one periods of wear were identified in the fifteen recordings, the median length of wear period was five days (IQR from three to seven days). The mean confidence in the identified starts and ends of periods of wear was 8.6 out of ten, with a standard deviation of 2.6. One period of wear, lasting two days was identified as having incorrect device orientation and the signals for the X and Z-axes were inverted to correct for this (see Figure 7.7).

The upright to sedentary posture transition algorithm identified a total of 4,293 transitions, sixteen falls and 4,277 normal (not known to be a fall) posture transitions. Figures 7.8 to 7.23 each show a plot of a fall and a similar normal upright to sedentary posture transition with the values for the eight features extracted from the signals. The fall ID in the caption of each figure can be cross-referenced with Table 6.8 for more information about each fall. Table 7.1 shows the results of statistical analysis on the continuous features (all except peak count which is ordinal) extracted from all 4,277 normal transitions and sixteen falls.

The Mann-Whitney U test showed impact magnitude and peak jerk were significantly higher for the falls and that there was a slightly greater separation between groups for peak jerk compared to impact magnitude (ρ=0.96 and 0.93, respectively). There was no significant difference between the groups for impact time (p=0.62). The results of the Mann-Whitney U test for peak count showed that there were significantly fewer peaks in the normal transitions compared to the falls (U=64191, ρ=0.94, $p<0.001$). Figure 7.24 shows (1) violin plots for impact magnitude, peak jerk and the impact time, and (2) a bar chart of the peak counts for the two groups. The plots highlight that while there are significant differences between the two groups for impact magnitude, peak jerk and peak count, there are also substantial overlaps in their distributions which could hinder classification. Figure 7.25 shows the percentage of events where the main impact peak was clipped for both normal transitions and falls.

Peak acceleration towards the ground, velocity and orientation change were significantly ($p<0.001$) higher for the falls compared to the normal transitions. Lead-time was significantly lower for the fall compared to the normal transitions ($p<0.05$) although the overlap between the groups was substantially greater for lead-time compared to other features (ρ=0.3). Figure 7.26 shows violin plots for peak acceleration towards the ground, velocity, lead-time and orientation change. The violin plots support the results of the Mann-Whitney U tests; they show that there is a separation between groups for peak acceleration towards the ground, vertical velocity and orientation change. Although there is overlap in the distributions the middle fifty percent of samples for each group occupy separate spaces. For lead-time, the majority of samples from both groups lie in the same range and there is no indication that this feature is useful for classification.

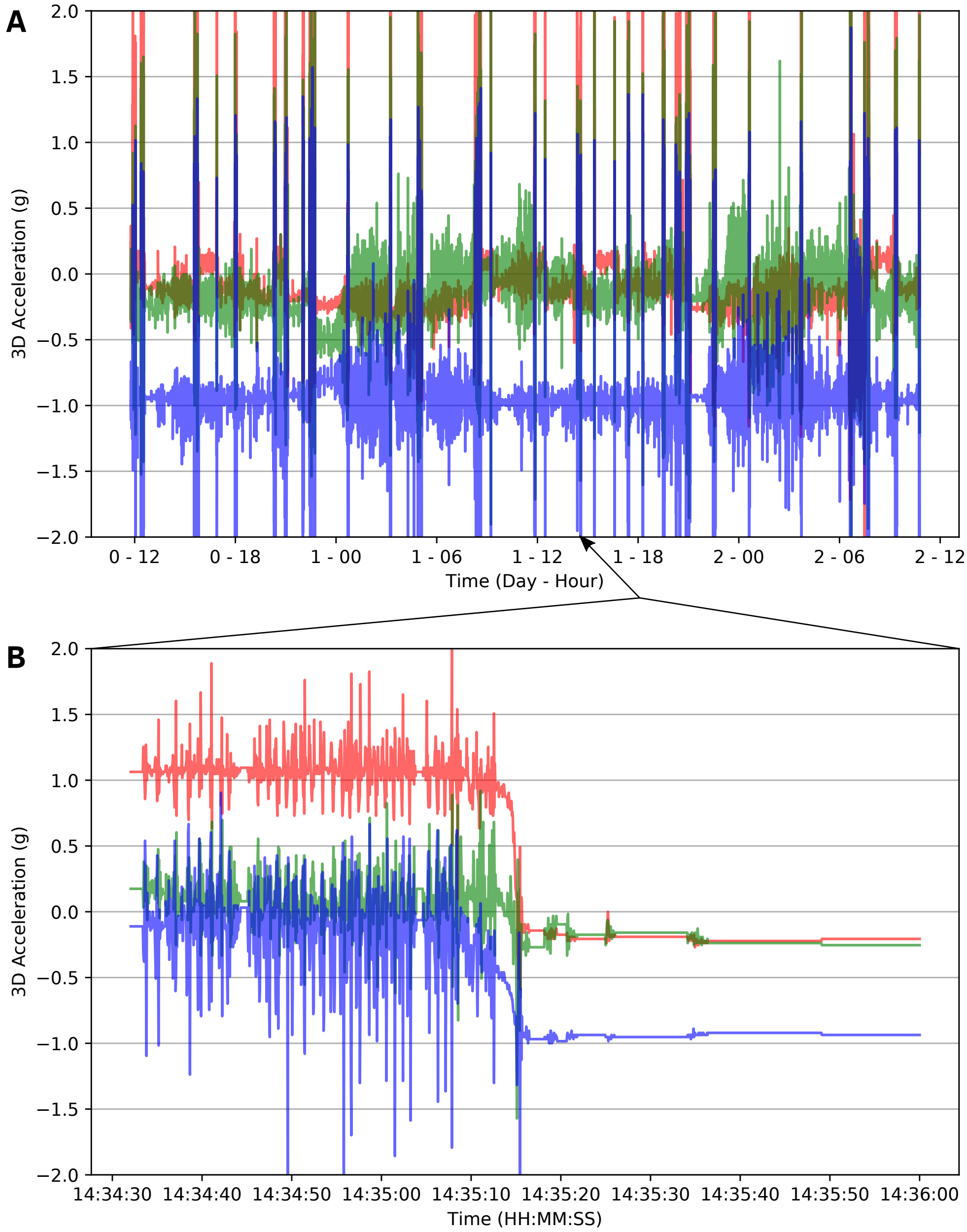


Figure 7.7: The wear period for which the device was worn incorrectly. **A** shows the entire wear period and **B** shows an extracted posture transition which is typical of those in this period of wear. For the majority of the time, the Z-axis (blue) is centred on -1 g (see **A**), when the device is worn correctly this indicates the wearer is lying on their front. Lying on the front for most of the day and night would be highly unusual, it is more likely that the wearer was either sitting (during the day) or lying on their back (at night). Therefore, the most likely explanation is that the device was rotated 180 degrees about the X-axis. When standing or walking the X-axis (red) should be approximately -1 g, when approximately +1 g the knee is above the hip. Therefore, one would normally expect to see periods where the X-axis is centred on -1 g, but not +1 g as in this period of wear. In addition, periodic spikes in the signal, such as those in **B** are indicative of walking and so the occurrence of these, when the X-axis is centred on +1 g, is highly unusual. The most likely explanation is that the device was rotated about the Z-axis in addition to the X-axis.

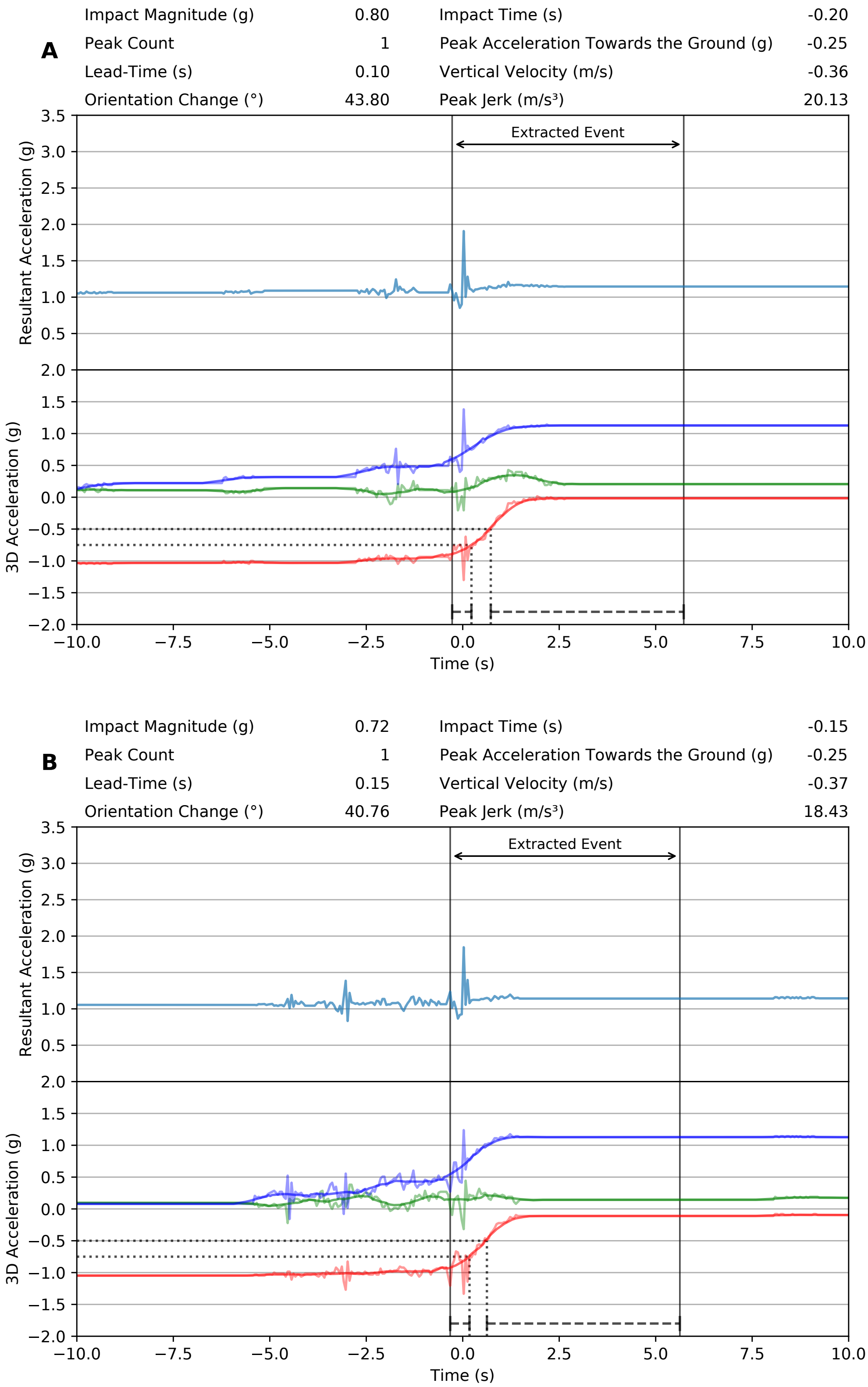


Figure 7.8: Fall versus normal posture transition 1 (fall ID 3). **A** shows a fall described in the incident report as: “Resident was found on the floor half sitting leaning against the wall on their right side in their bedroom toilet. Conscious and alert with no injury noted at the time.”. **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

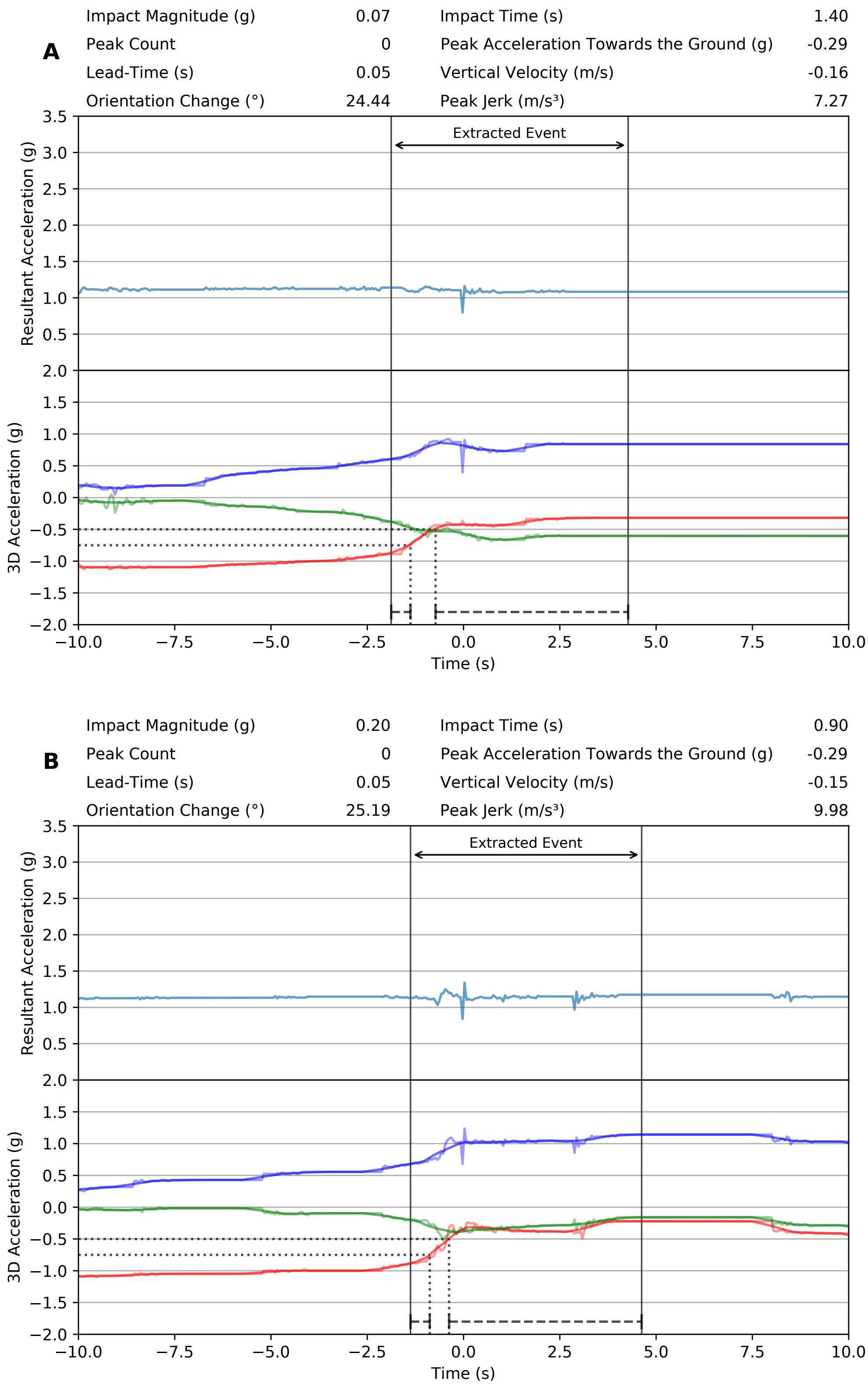


Figure 7.9: Fall versus normal posture transition 2 (fall ID 4). **A** shows a fall described in the incident report as: "Unwitnessed fall, sensor mat alerted staff. Resident was found sitting on their bedroom floor beside the toilet door, they said they tripped on way to the toilet.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

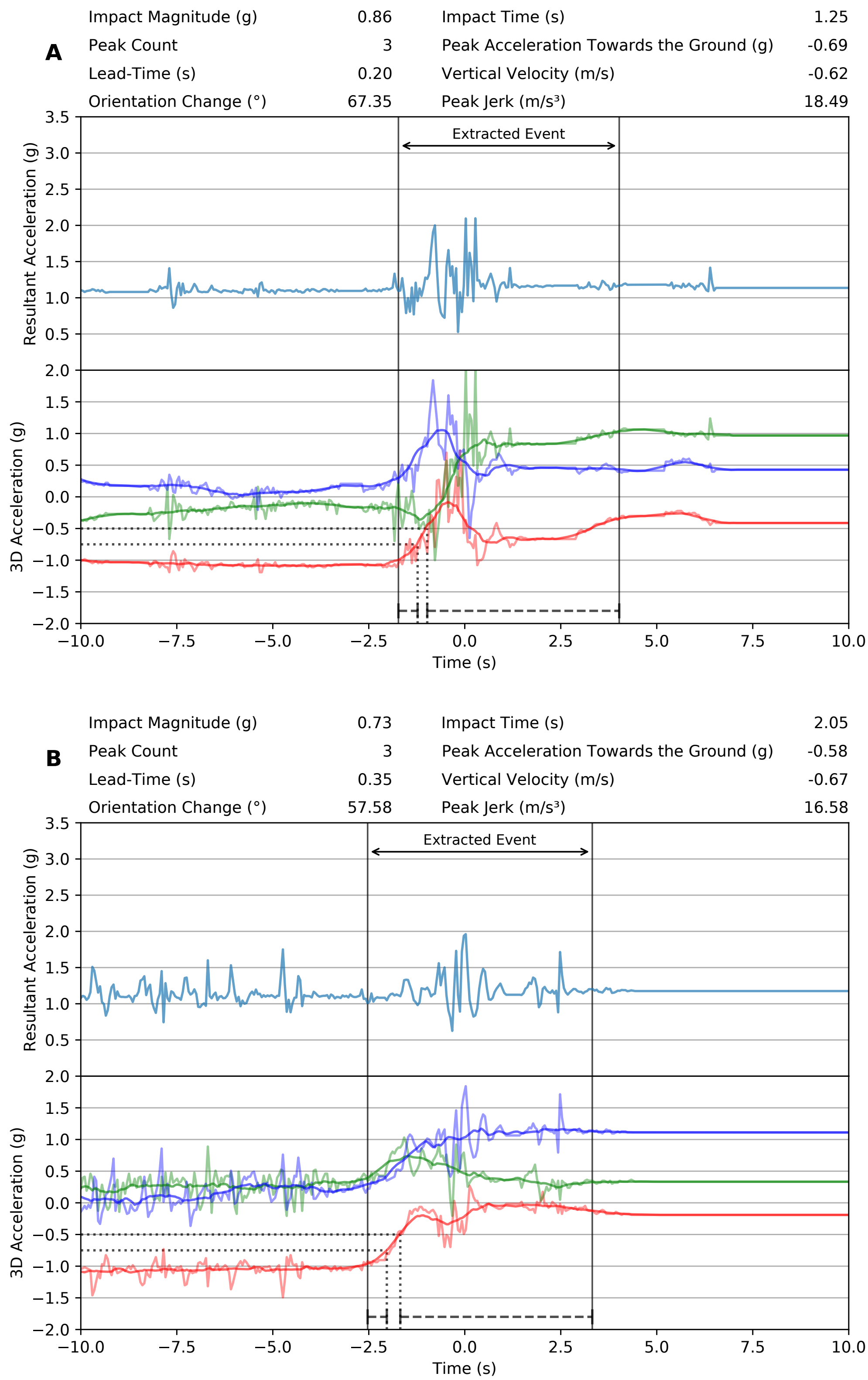


Figure 7.10: Fall versus normal posture transition 3 (fall ID 6). **A** shows a fall described in the incident report as: “Resident was found on the floor in the lounge. No falls details known.”. **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

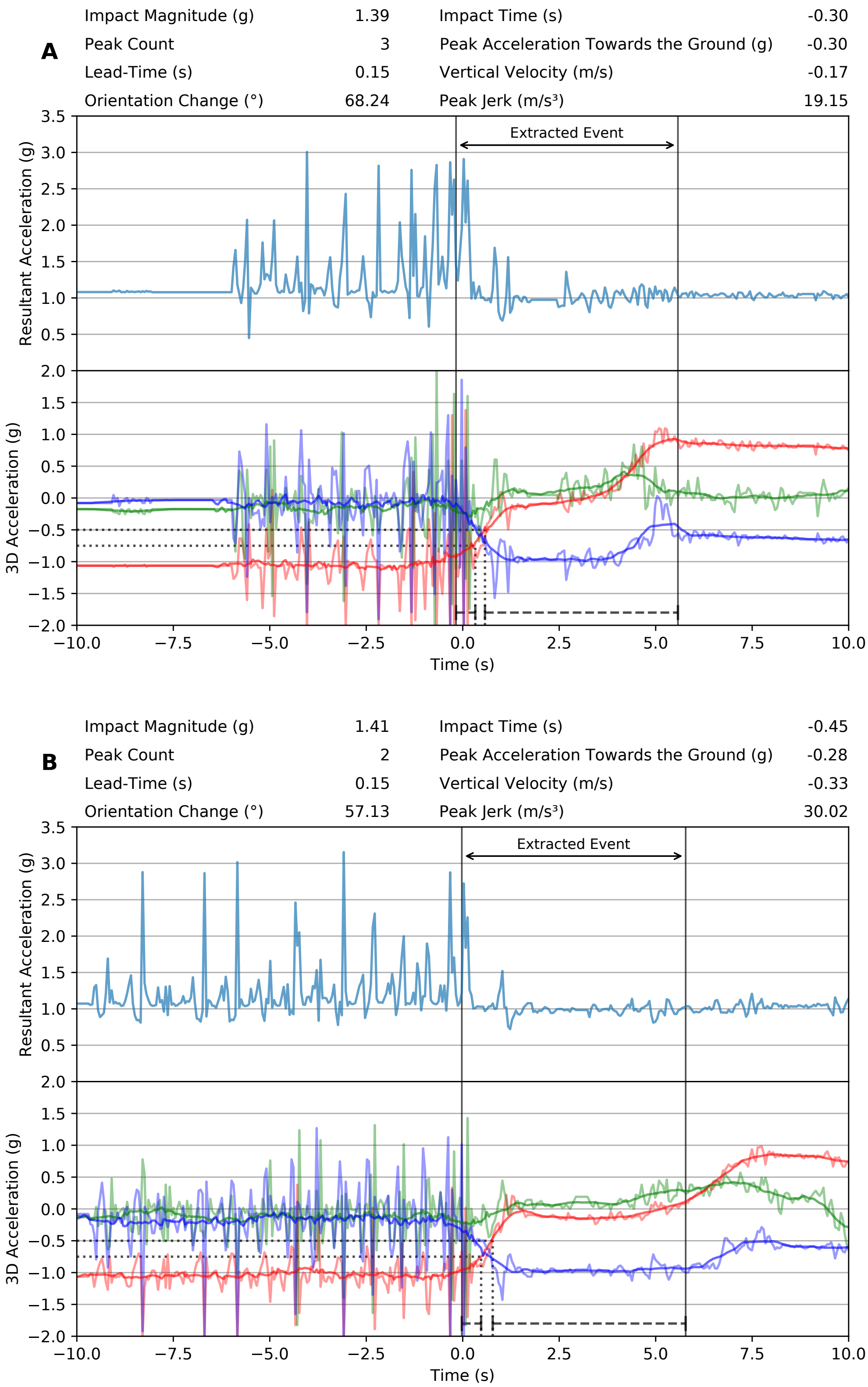


Figure 7.11: Fall versus normal posture transition 4 (fall ID 10). **A** shows a fall described in the incident report as: "Found on the floor by staff after their alert mat went off. Resident appeared more confused than usual due to chest infection. Abrasion on arm noted.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

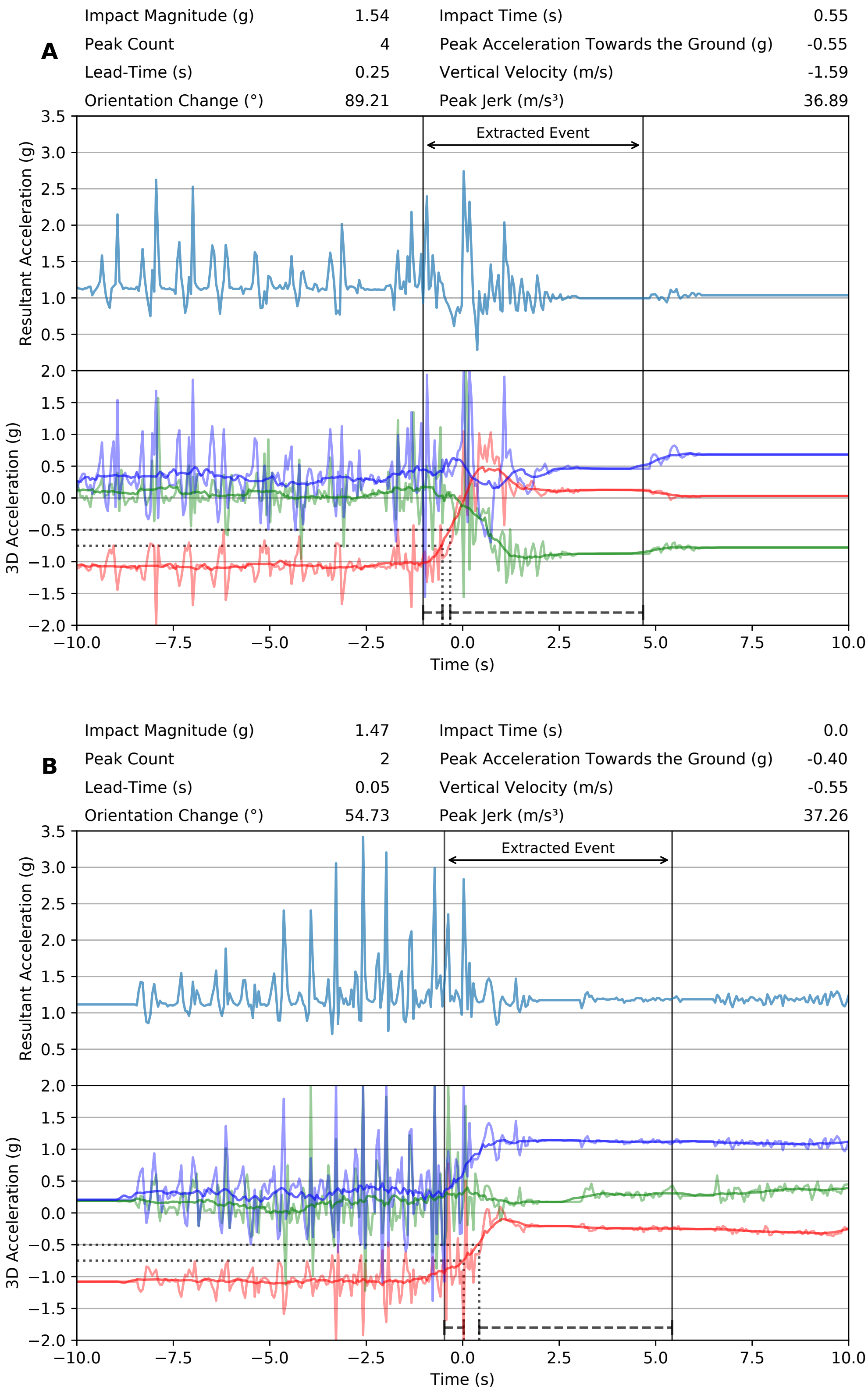


Figure 7.12: Fall versus normal posture transition 5 (fall ID 11). **A** shows a fall described in the incident report as: "Found on the floor in their bedroom. Resident's alert mat had alerted staff to attend, but on arrival, the resident was already on the floor. Resident was trying to get something out of their drawer.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

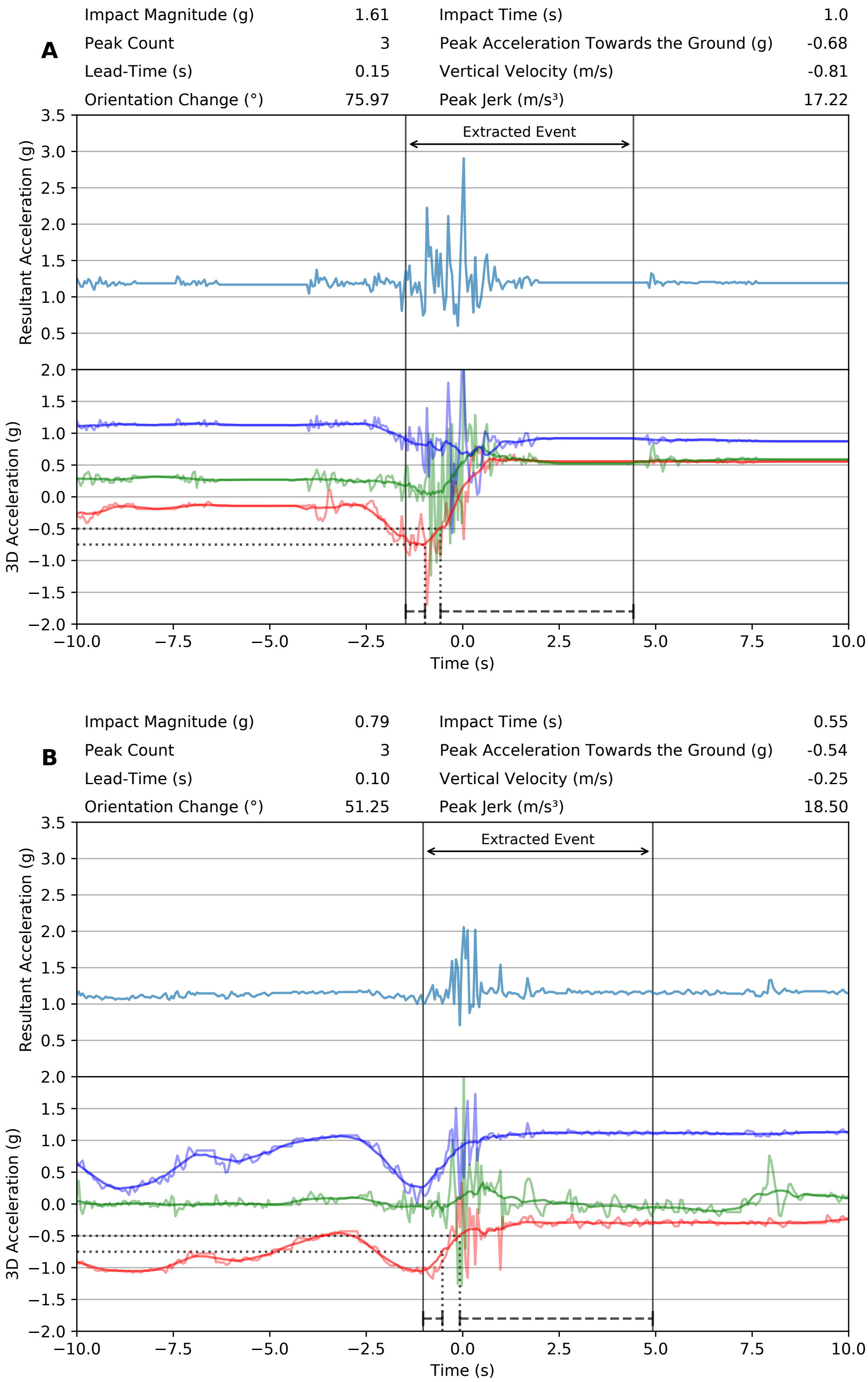


Figure 7.13: Fall versus normal posture transition 6 (fall ID 12). **A** shows a fall described in the incident report as: "Resident got up from the chair they were sitting in, lost their balance and fell.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

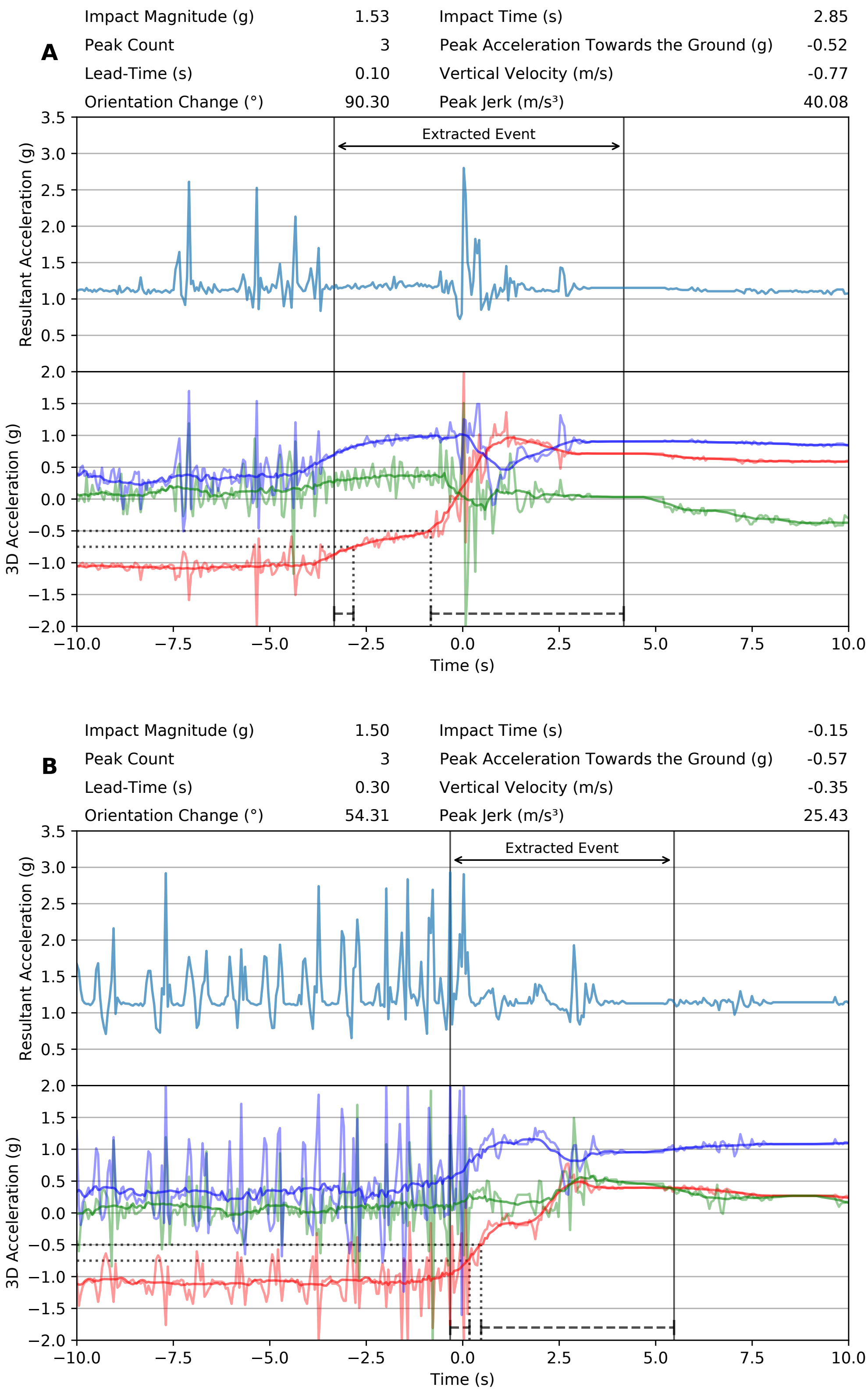


Figure 7.14: Fall versus normal posture transition 7 (fall ID 13). **A** shows a fall described in the incident report as: "As staff were supervising resident to sit in the chair they overbalanced, resulting in them sliding to the floor.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

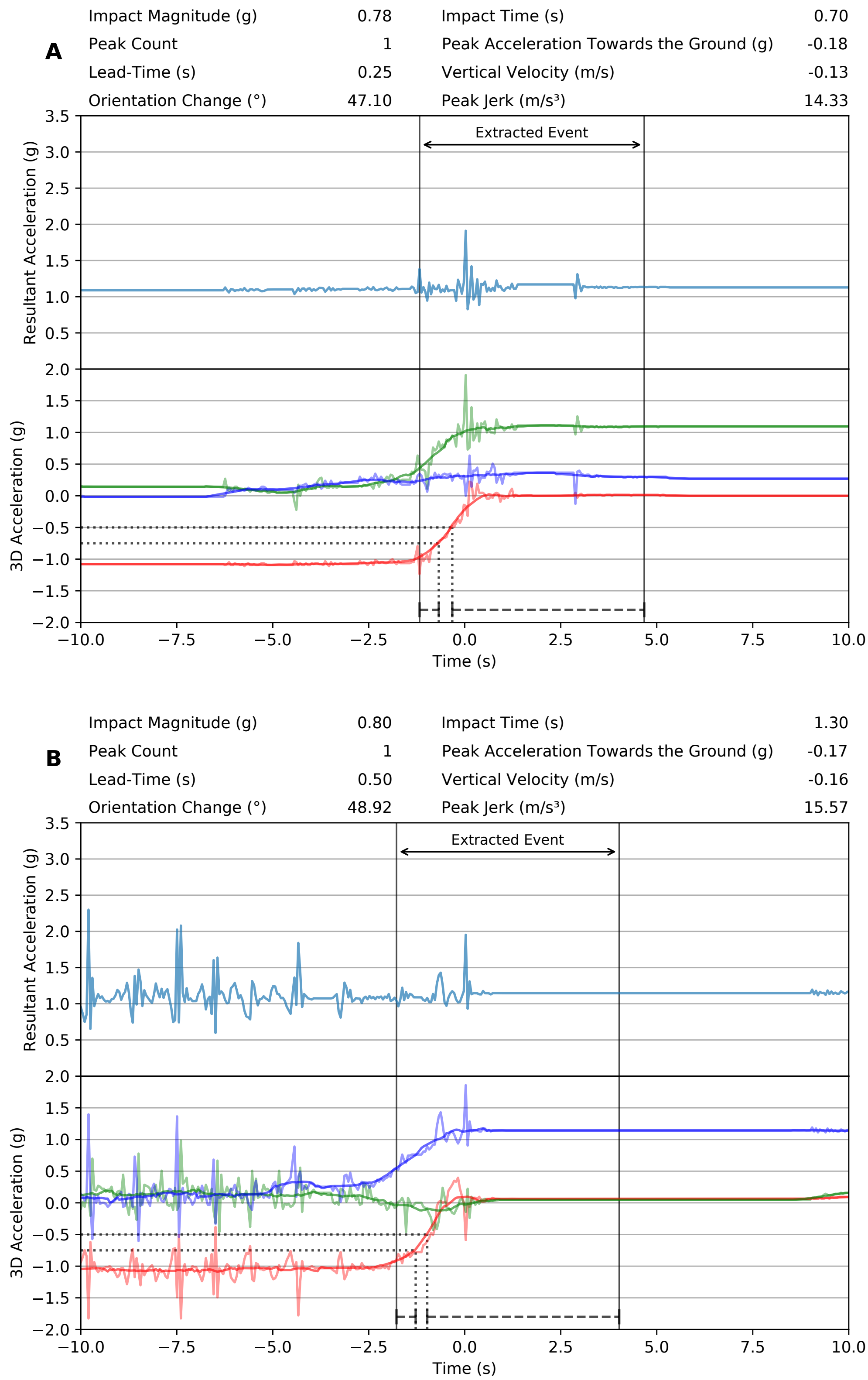


Figure 7.15: Fall versus normal posture transition 8 (fall ID 14). **A** shows a fall described in the incident report as: "Resident was cleaning up a spill from their floor and tipped onto their bottom.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

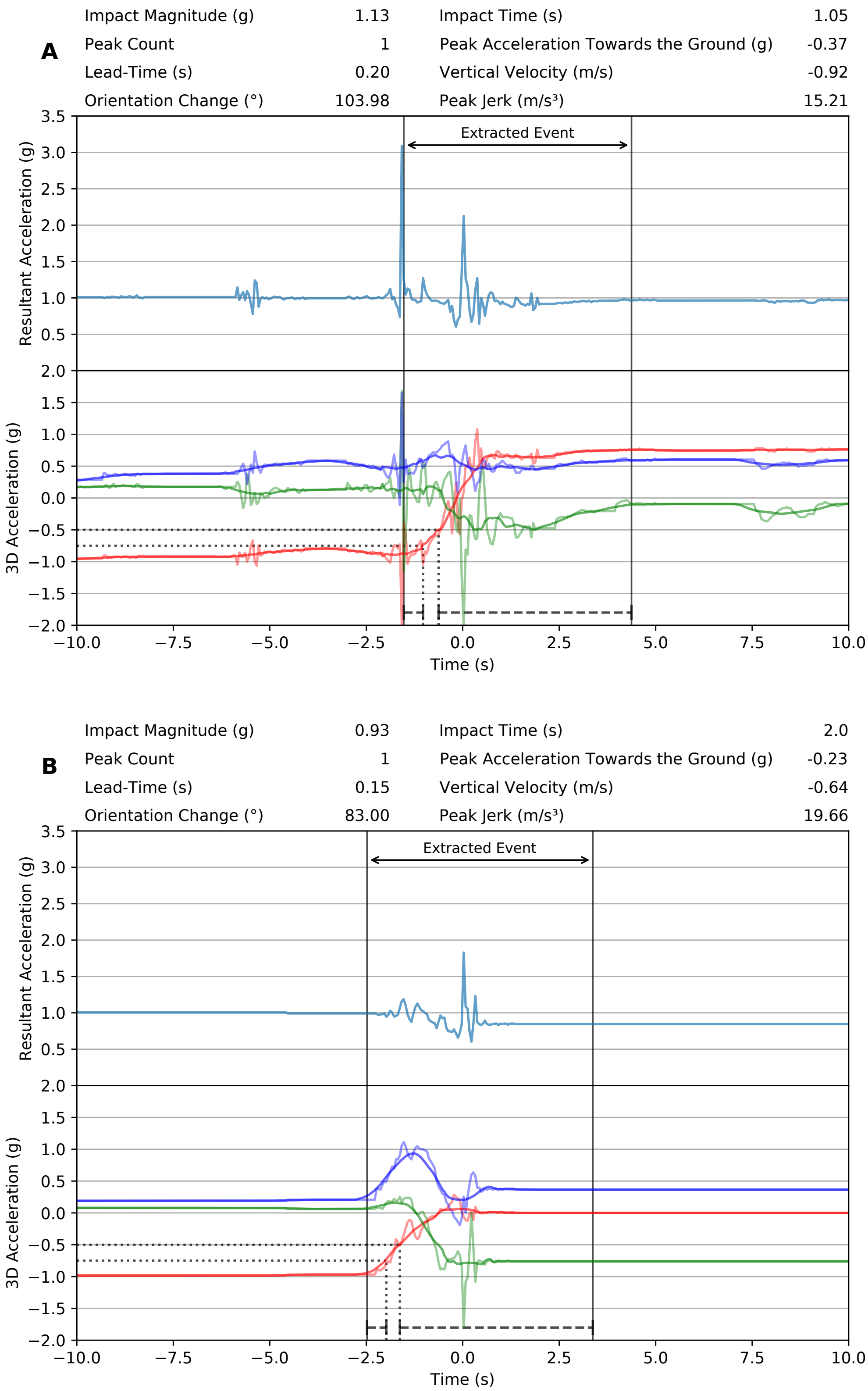


Figure 7.16: Fall versus normal posture transition 9 (fall ID 19). **A** shows a fall described in the incident report as: “Resident was lying on the floor near their bed. They said they lost their balance while trying to reach the wardrobe.”. **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

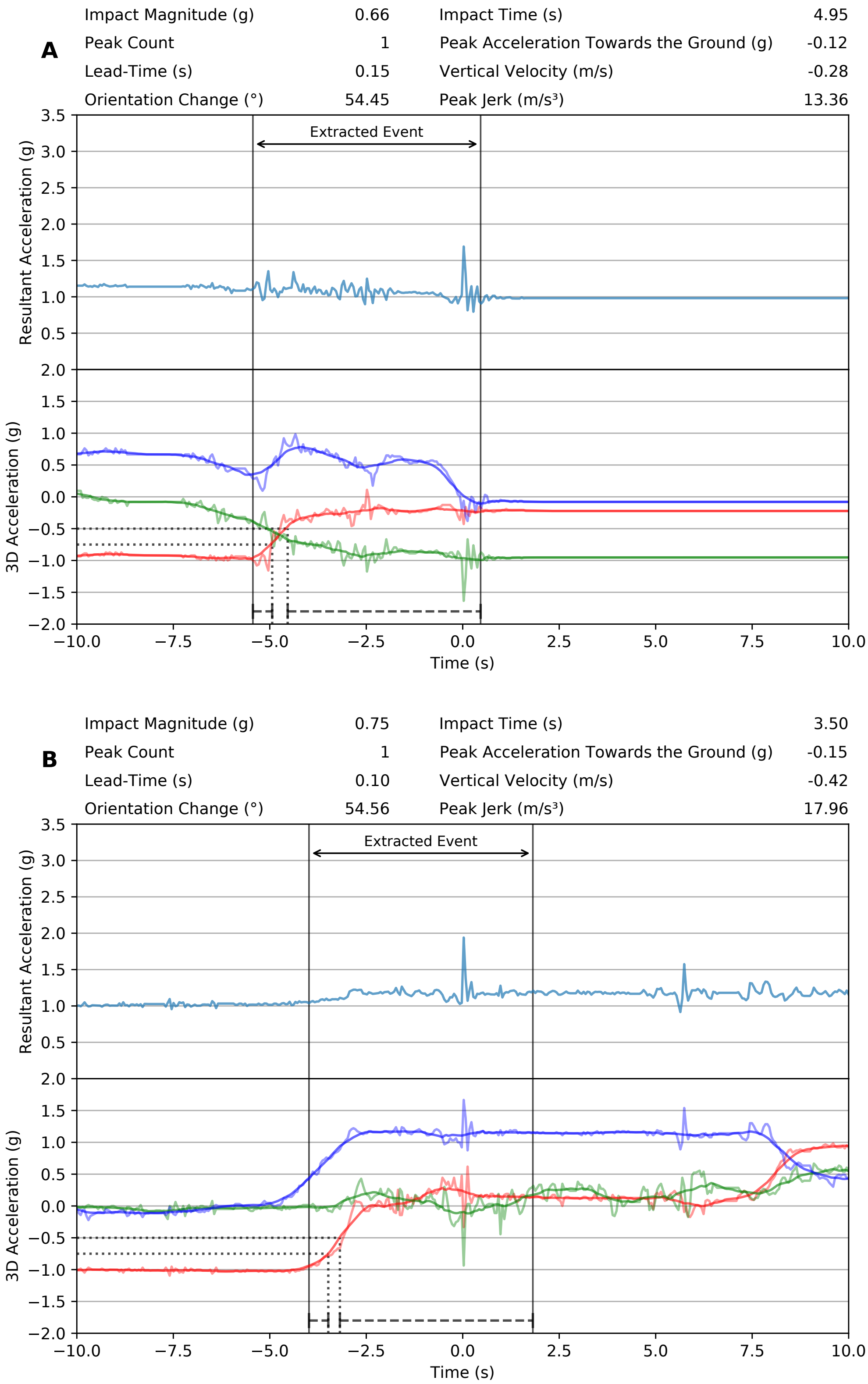


Figure 7.17: Fall versus normal posture transition 10 (fall ID 23). **A** shows a fall described in the incident report as: “Resident was found lying on the floor by staff. Staff reported that the resident was in bed when they did the routine night check about 10 min before. Resident didn’t know how they ended up on the floor. They were not sure whether they hit their head or not.”. **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

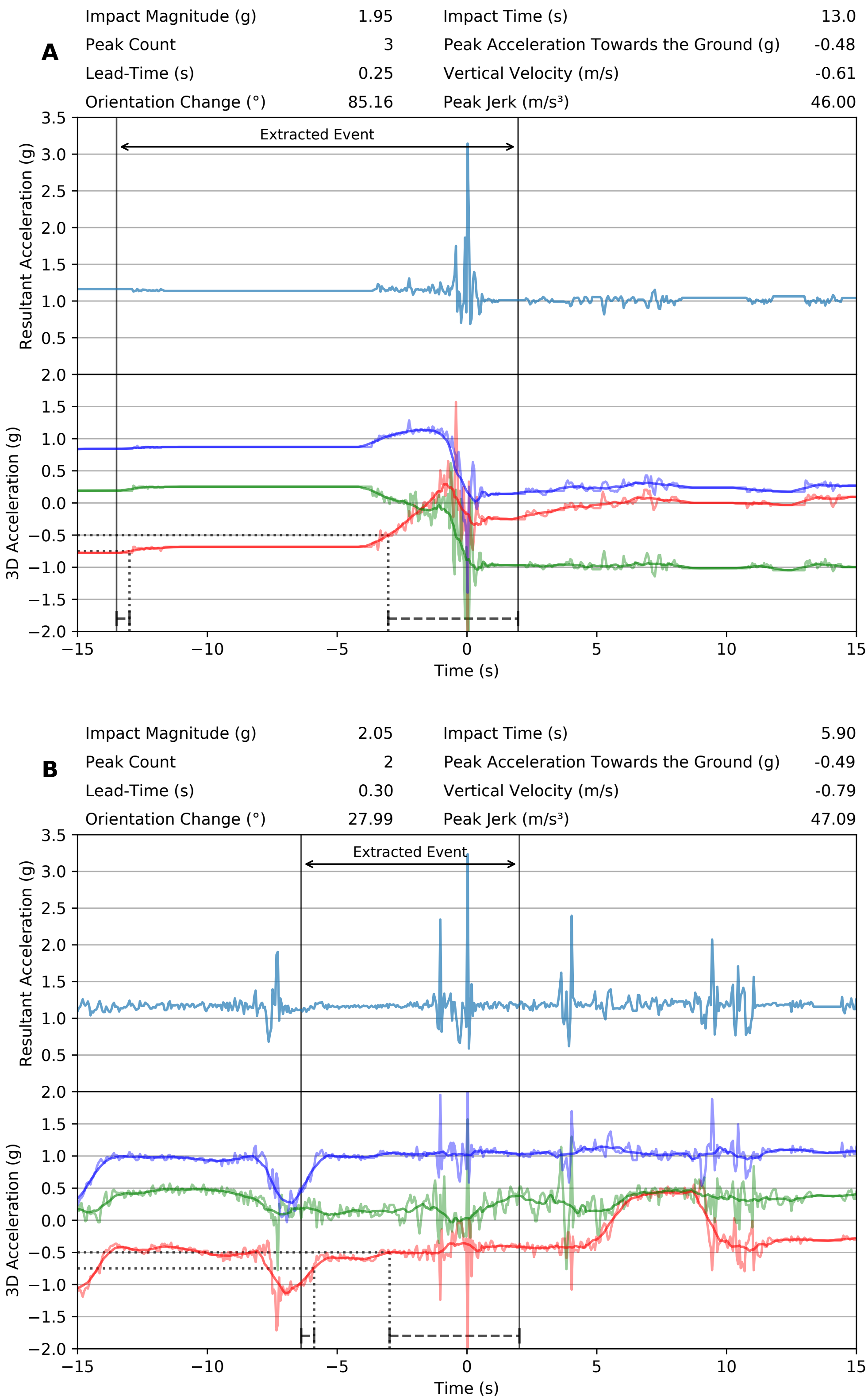


Figure 7.18: Fall versus normal posture transition 11 (fall ID 24). **A** shows a fall described in the incident report as: “Resident found on the floor in the bathroom after calling for help.”. **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

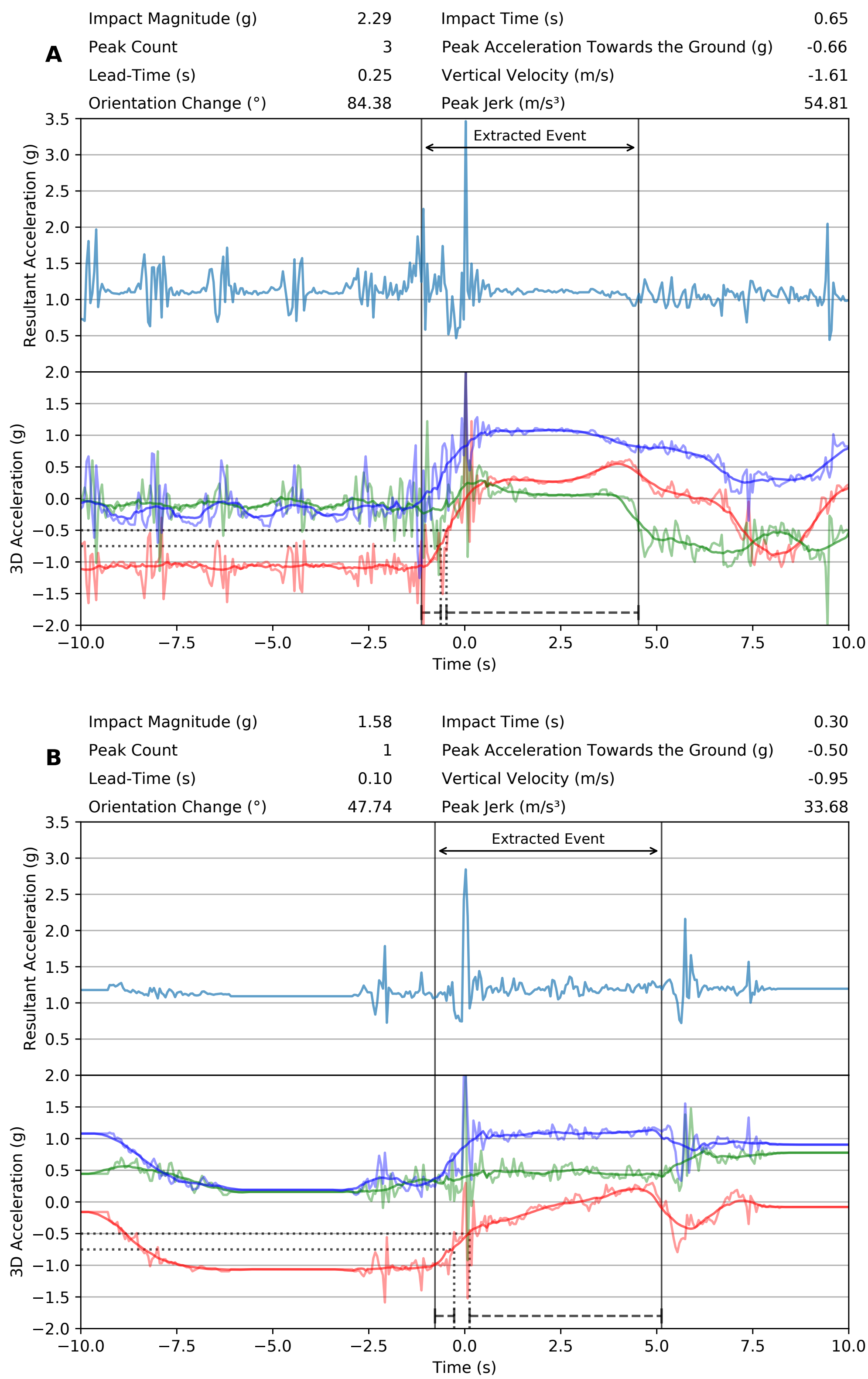


Figure 7.19: Fall versus normal posture transition 12 (fall ID 26). **A** shows a fall described in the incident report as: "Resident was walking for their tea, misjudged their footing and fell to the ground. Staff and another resident witnessed fall.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

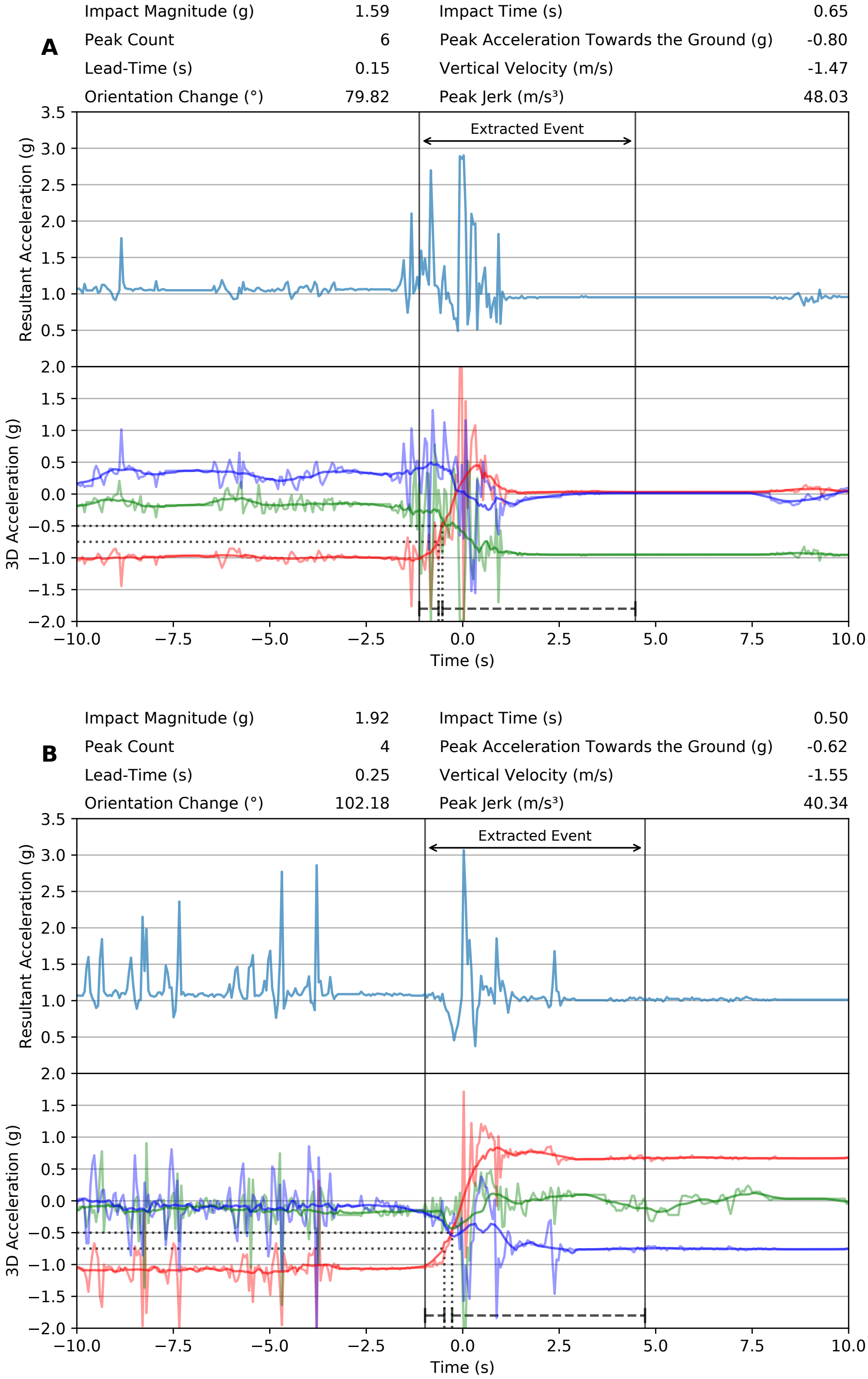


Figure 7.20: Fall versus normal posture transition 13 (fall ID 28). **A** shows a fall described in the incident report as: “Resident was found on their bedroom floor.”. **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

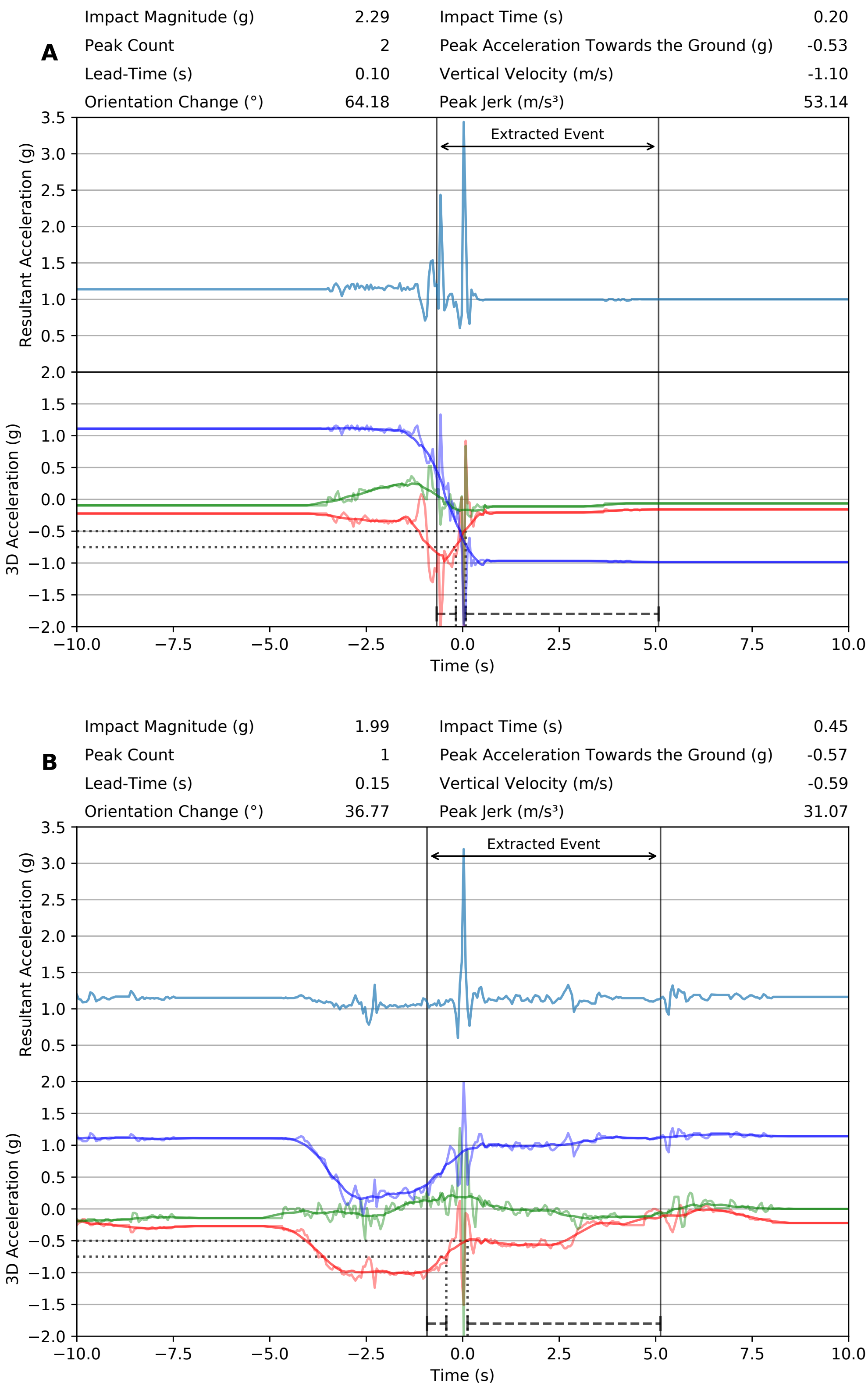


Figure 7.21: Fall versus normal posture transition 14 (fall ID 29). **A** shows a fall described in the incident report as: "Resident had an unwitnessed fall whilst in the conservatory.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

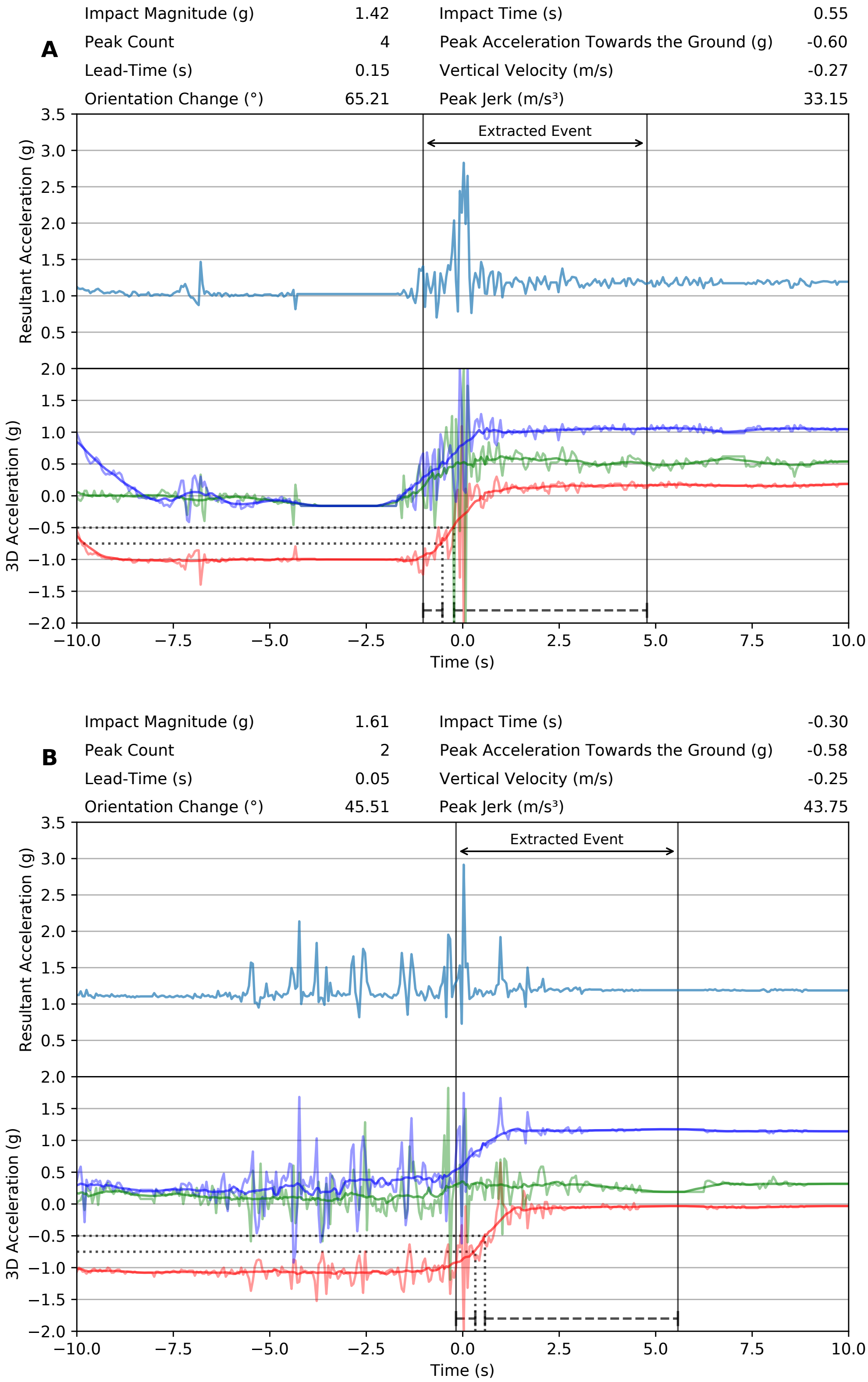


Figure 7.22: Fall versus normal posture transition 15 (fall ID 31). **A** shows a fall described in the incident report as: "Resident buzzed as they had lost their balance trying to get on to the toilet.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

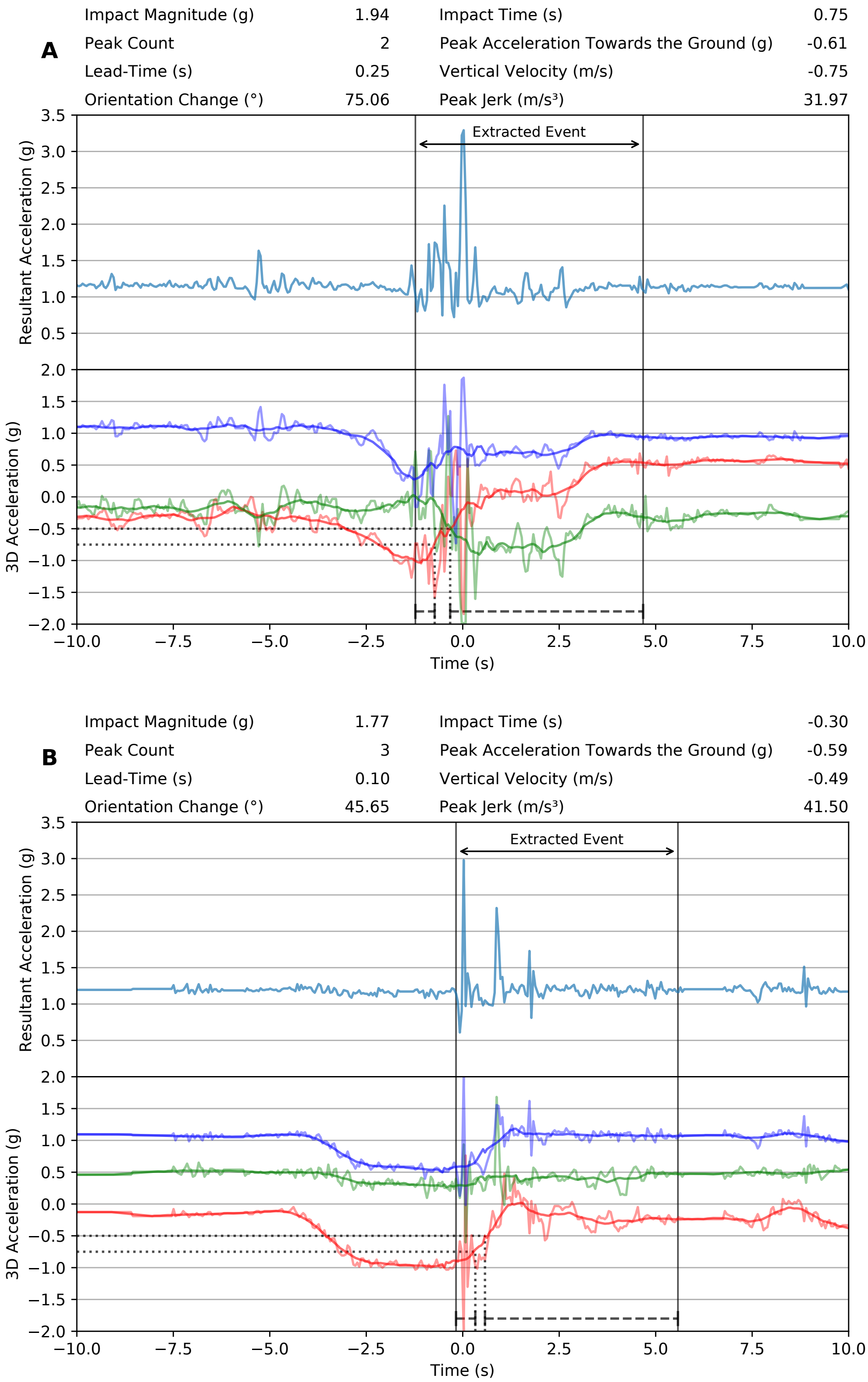


Figure 7.23: Fall versus normal posture transition 16 (fall ID 32). **A** shows a fall described in the incident report as: "Resident was found sitting on their bedroom floor, they stated that as they went to stand their left leg gave way.". **B** shows a normal upright to sedentary transition which is similar to the fall. On the 3D acceleration plots the darker lines are the moving average filtered signals and the lighter lines are the raw accelerometer signals.

Table 7.1: Characteristics of falls and normal upright to sedentary posture transitions.

	Min	**LQ**	**Median**	**UQ**	**Max**	**Mann-Whitney U**		
						U	**ρ**	**p-value**
Impact Magnitude (g)								
Fall	0.07	0.84	1.48	1.70	2.29	63601	0.93	<0.001
Normal	0.01	0.13	0.24	0.40	2.05			
Peak Jerk (m/s^3)								
Fall	7.27	16.71	26.05	41.56	54.81	65918	0.96	<0.001
Normal	0.00	2.30	4.14	7.10	47.09			
Impact Time (s)								
Fall	-0.30	0.55	0.72	1.29	13.00	41242	0.60	0.62
Normal	-0.45	0.35	0.55	1.10	31.10			
Peak Acceleration Towards the Ground (g)								
Fall	0.12	0.30	0.53	0.62	0.80	64818	0.95	<0.001
Normal	0.00	0.06	0.09	0.15	0.89			
Vertical Velocity (m/s)								
Fall	0.13	0.28	0.69	0.96	1.61	61744	0.90	<0.001
Normal	0.00	0.06	0.12	0.21	1.55			
Lead-Time (s)								
Fall	0.05	0.14	0.15	0.25	0.25	20435	0.30	<0.05
Normal	0.05	0.15	0.25	0.60	4.20			
Orientation Change (°)								
Fall	24.44	61.75	71.65	84.57	103.98	59899	0.88	<0.001
Normal	3.32	33.45	40.23	47.68	151.95			

Note: N = 16 falls and 4,277 normal transitions. LQ = Lower Quartile, UQ = Upper Quartile. ρ is the U score normalised to between 0 and 1 by dividing U by its maximum value (N falls $\times$ N Normal transitions), it is a measure of overlap between the two distributions. A ρ of 0 indicates all the samples in the fall group where lower than those in the normal group, 0.5 indicates complete overlap and 1 indicates all the samples in the fall group were higher than those in the normal group.

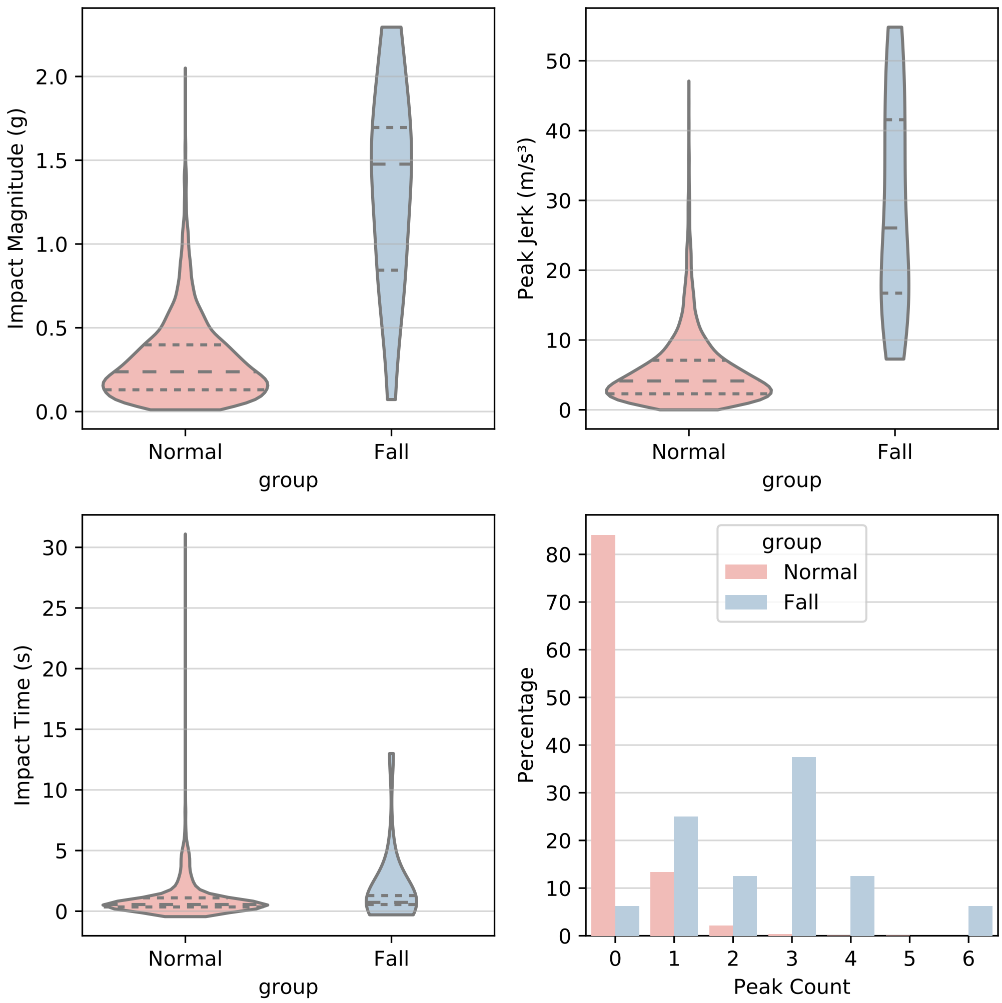


Figure 7.24: Distributions for impact-related features. For the violin plots, the dashed lines show the median, the dotted lines show the lower and upper quartiles and the head and tail of the violin denote the minimum and maximum values. The area of each violin is normalised by sample size for each group.

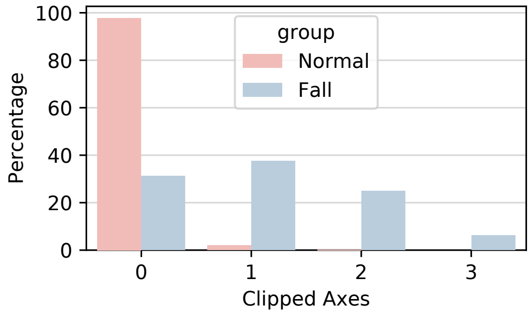


Figure 7.25: The percentage of events where none, one, two or three of the axes were clipped at the main impact peak for both normal transitions and falls. Ninety-three of the normal upright to sedentary posture transitions and eleven of the falls had a clipped signal on one or more axes.

Figure 7.27 and Figure 7.28 both show the interactions between features; Figure 7.27 shows the distribution for each group for each pair of features and Figure 7.28 shows the Pearson product-moment correlation coefficients for each pair of features. There were similar correlations for both groups between impact magnitude, peak jerk, peak acceleration towards the ground, vertical velocity and peak count. The correlation between impact magnitude and peak jerk was the strongest of all the pairings. Orientation change was the only feature for which there were correlations for the falls but not the normal transitions; correlations between orientation change and all other features were observed only for the fall group. There are four fall samples (fall ID: 3, 4, 14 and 23) which occupy a space close to the densest area of normal transitions, these would present a major challenge for classification.

7.7 Discussion

This study aimed to identify characteristics which are unique to falls and understand why existing wearable fall detection technology has not achieved an acceptable balance between sensitivity and precision. To achieve this aim, the most comprehensive analysis to-date of real-world fall signals was conducted. This was the first study to use posture classification as a method to select periods of interest for analysis as a possible fall or fall-like motion. This was also the first study to analyse the interaction between features extracted from the signals and gain an understanding of which combinations were most valuable in separating falls from normal movements.

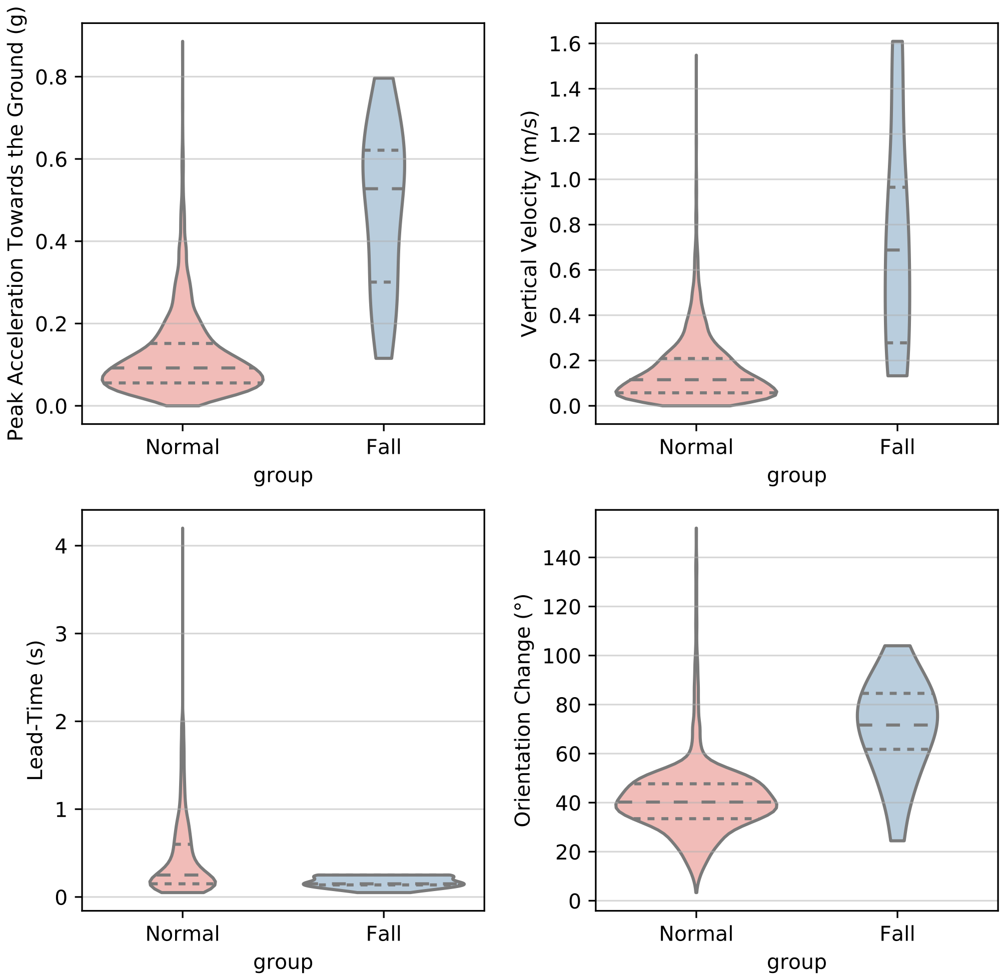


Figure 7.26: Distributions of peak acceleration towards the ground, vertical velocity, lead time and orientation change. The dashed lines show the median, the dotted lines show the lower and upper quartiles and the head and tail of the violin denote the minimum and maximum values. The area of each violin is normalised by sample size for each group.

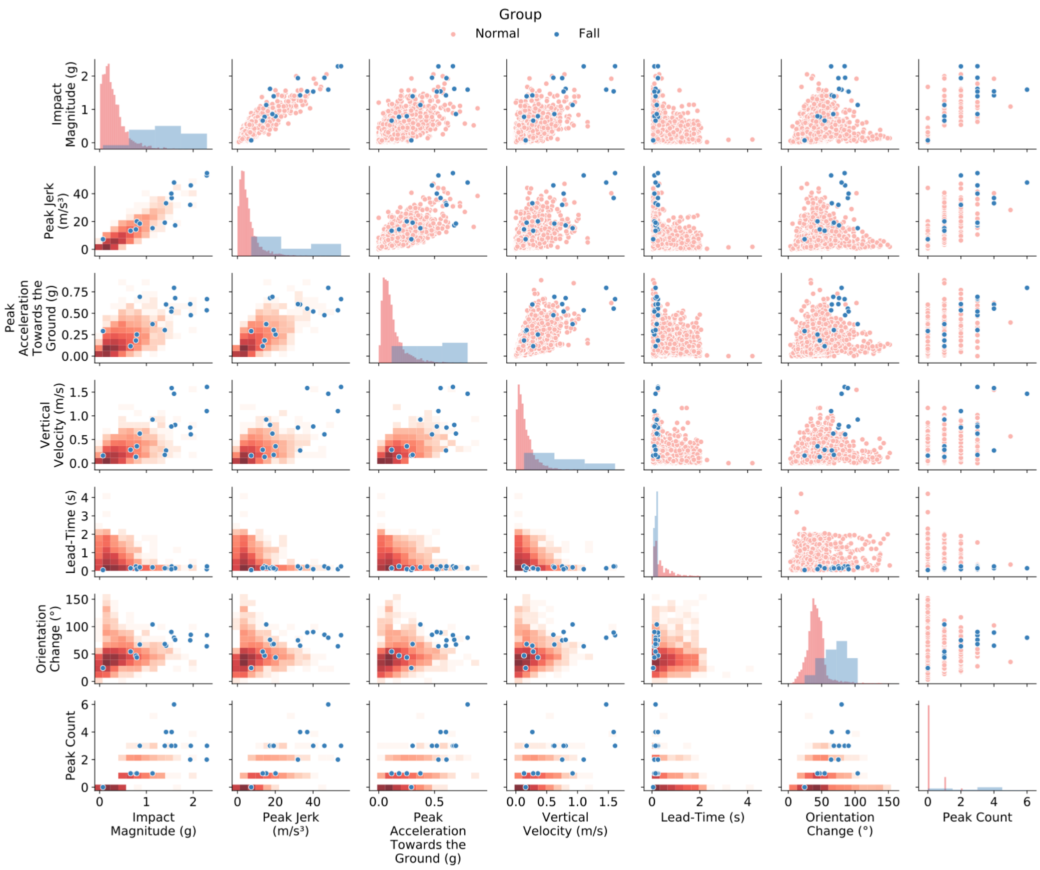


Figure 7.27: Interactions between features where a significant difference between groups was found. The diagonal axes show histograms for each feature, the top-right axes show scatter plots for every pairing of the features and the bottom-left axes show a scatter plot for the fall group overlaid on a density map for the normal transition group. The area of the histograms is normalised by sample size for each group.

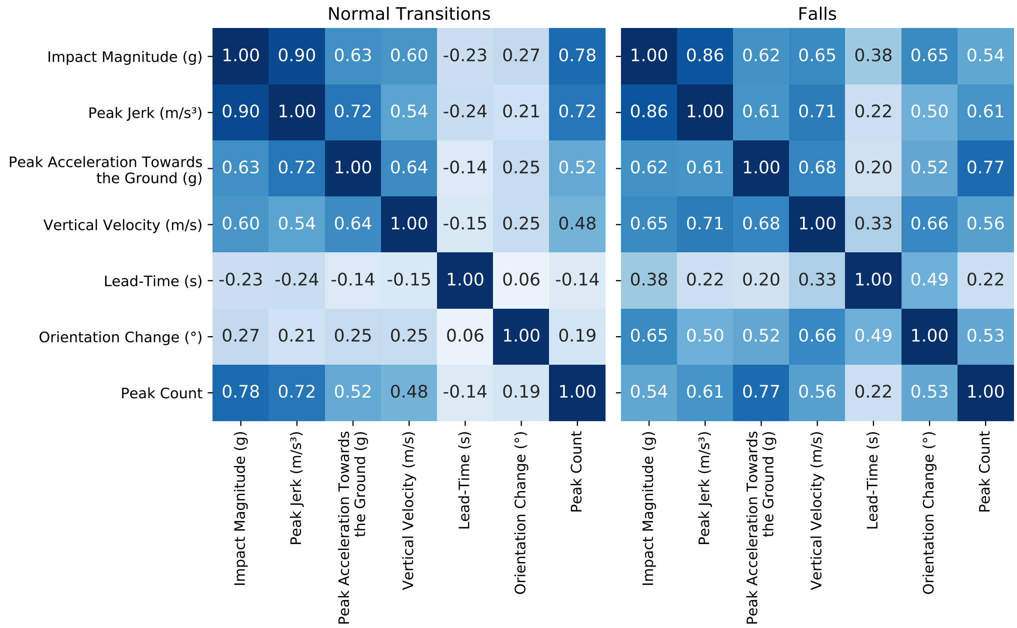


Figure 7.28: Pearson product-moment correlation coefficients for each pairing of features for both falls and normal upright to sedentary transitions. Only features for which there was a significant difference between groups are included. Strong correlations indicate that little information is gained by using both features over just one of them.

Features were extracted from 4,277 upright to sedentary transition signals and sixteen fall signals recorded with a thigh-worn triaxial accelerometer. Eight features were extracted from the signals and the ability to distinguish falls from normal upright to sedentary transitions based on each feature was evaluated. Significant differences between the two groups were found for seven out of eight features, however, the analysis also revealed that the distributions overlap for all of the features extracted in this study. The sections which follow discuss the results for each feature, what the findings reveal about the performance of previously developed wearable fall detection and the implications for future research.

7.7.1 Interpretation of Results

The results of the current study are similar to those of Bourke et al. [114] for the following features which were common to both studies: impact magnitude, peak acceleration towards the ground and lead-time. The current study focused on upright to sedentary posture transitions whereas Bourke et al. [114] included all types of motion which may affect the results. However, since approximately three-quarters of falls appear to be from an upright to a sedentary posture, one would expect the results to be similar. Bourke et al. [114] had a larger number of falls (n = 100) than the current study (n = 16) but less ADL samples despite the less restrictive method of event selection (n = 1,908 and 4,277 respectively). The data used by Bourke et al. [114] were collected in a hospital geriatric rehabilitation unit rather than care homes, which may explain the difference in fall to ADL ratio. The rate of falls over time cannot be compared as Bourke et al. [114] did not provide this.

Bourke et al. [114] found some falls with higher impact magnitude, which would be expected given (1) that all the data in the current study and only an undisclosed portion of their data were collected with sensors limited to ±2 g, and (2) that the impact peak was clipped in eleven of the falls in the current study. The current study included a fall (fall ID 3) with a much lower impact magnitude than any included in the study by Bourke et al. [114] (minimum of 0.07 g and 0.62 g respectively, once adjusted to account for differing methods). This low impact fall occupies the space where there is the densest grouping of normal upright to sedentary transitions for all features, making it hard to detect as a fall without an extremely high number of false positives. This type of fall could be viewed as rare, given Bourke et al. [114] did not find any falls with such low impact. However, both studies have found falls with relatively low impacts which are hard to distinguish from other movements based on the common methods of vertical motion and impact analysis.

From the analysis of Bourke et al. [114], it is not possible to determine if the low impact falls could be distinguished from other movements based on the remaining features. However, it is unlikely that a low impact fall would have a high peak acceleration towards the ground, vertical velocity or peak jerk and the distributions for the other two features common to both studies, peak acceleration towards the ground and lead-time, were similar in both studies. For peak acceleration towards the ground, the results were comparable, although the peak acceleration towards the ground for the falls group tended to be lower in the current study (0.3 - 0.53 - 0.62 g versus 0.51 - 0.66 - 0.8 g for lower quartiles, medians and upper quartiles respectively). For lead-time, Bourke et al. [114] found a greater difference between groups, as the median lead-time for their ADL group was higher compared to the normal upright to sedentary transition group in the current study (1.08 s versus 0.25 s respectively), but there was substantial overlap between groups for both studies. Some long lead-times (up to 4.2 s) were found in the current study, which Bourke et al. [114] did not find due to their hard limit of two seconds between the pre-impact nadir and main impact peak, without the flexibility to extend the two-second window to ensure the true nadir was found, as in the current study.

This study was the first to compare vertical velocity at the point of impact for falls and normal upright to sedentary transitions using real-world data. The results showed vertical velocity was significantly higher for the falls compared to normal upright to sedentary transitions. Since vertical velocity is the combination of vertical acceleration and time, it is related to peak acceleration towards the ground and the results showed a correlation between the two. Peak acceleration towards the ground appears to be better for fall detection as there was a greater separation between groups ($\rho = 0.9$ and 0.95 for vertical velocity and peak acceleration towards the ground respectively).

Peak jerk had previously been used to compare simulated and real backwards falls, and significant differences were found [15], however, no study had previously investigated whether peak jerk could be used to detect falls. The results of the current study showed that peak jerk was the best feature to distinguish falls from normal upright to sedentary transitions ($\rho = 0.96$). Peak jerk was strongly correlated with impact magnitude (r = 0.9 and 0.86 for the normal and fall groups, respectively). This correlation was likely due to a combination of high impacts giving greater potential for a high jerk, the sample rate not being high enough to fully capture the shape of the impact peak and the limited range of the sensor (± 2 g) leading to clipped peaks for eleven of the falls. It is possible that the true peak occurred between samples or was clipped due to the limited range of the sensor, the true peak could, therefore, be both higher and have a steeper leading edge than that which the sensor captured.

There is a phenomenon known as the curse of dimensionality whereby the amount of data required to train a robust model often grows exponentially with dimensionality. The phenomenon occurs because as dimensionality increases the volume of the feature space increases and the data become sparse, this makes it relatively easy to fit a model which divides the space for classification, however, there is a high risk that the model may be over-fitted and not generalise to unseen data [186]. Since there has consistently been extremely limited real-world fall data available for the development of fall detection, the number of features needs to be controlled to avoid the curse of dimensionality. If the finding of a high correlation between impact magnitude and peak jerk is supported by future studies, developers should consider only using one of these. In addition to the correlation between impact magnitude and peak jerk, there were correlations, albeit weaker ones, between all of the following features: impact magnitude, peak jerk, peak count, peak acceleration towards the ground and vertical velocity. As research yields new features which can be used for fall detection, developers should consider only using a subset of these features which characterise vertical motion and impact.

This study is the first to devise a method to count impacts and assess the use of impact count as a feature to distinguish falls from other movements. The results showed that multiple impacts are rare in normal upright to sedentary transitions ($n = 109$ or 2.5 percent), but present in almost seventy percent ($n = 11$) of falls (Figure 7.24). Therefore, the use of an impact count for fall detection shows promise and warrants further investigation in future studies. The method used in this study was relatively simple and used an arbitrary peak height threshold of 0.5 g for a peak to be counted as an impact. There is, therefore, considerable scope to refine the method of selecting peaks to count as an impact which may improve the separation between falls and normal upright to sedentary transitions.

In addition to simply counting impacts, there is the potential to engineer features to characterise any secondary or tertiary impacts, or engineer features which combine impacts into single features, for example, total impact magnitude as the sum of all impact peak magnitudes. The analysis of secondary and tertiary impacts could not be added to the current study without increasing the risk of type I errors due to a high number of tests on a small sample of falls. However, impact count was shown to be a useful feature, although 109 (2.5 percent) normal posture transitions had multiple impacts. Analysis of secondary or tertiary impacts may reveal features which are necessary to distinguish between the normal transitions with multiple impacts and the falls. Hence, such analysis combined with refinements to the identification of impacts has great potential to improve fall detection performance.

This was the first study to analyse differences in the change in orientation of the thigh between falls and normal upright to sedentary transitions. The results showed that the orientation change in the recorded falls was significantly greater ($p<0.001$) compared to the normal upright to sedentary transitions. The findings for thigh orientation change in the current study were similar to those of Bourke et al. [114]. For the maximum torso angle from vertical, Bourke et al. [114] also found that falls had a significantly greater maximum angle, and in both studies the fall group showed a positive skew and the other group showed a negative skew with overlapping distributions. Direct comparison between studies is not possible due to the different sensor locations.

The data showed a correlation between orientation change and impact magnitude, peak jerk, peak acceleration towards the ground and vertical velocity only for the falls and not the normal upright to sedentary transitions. The difference in correlation between groups for orientation change, combined with the significant differences between groups for these aforementioned features, suggests that the combination of orientation change with characteristics of vertical motion and impact should lead to relatively good separation between groups, compared to other combinations of features where the correlation for both groups was similar. Indeed, analysis of how orientation change interacts with other features revealed that the combination of a high orientation change combined with a high impact magnitude, peak jerk, peak acceleration towards the ground or vertical velocity is rare for normal transitions but relatively common for falls. These combinations appear to give the greatest separation between groups (see Figure 7.27), although only eight of the falls sit clearly separate, except for a pair of outliers, from the normal upright to sedentary transitions.

7.7.2 Insights into the Performance of Previously Developed Wearable Fall Detection

The findings of this study provide insight into the performance of fall detection which has been developed previously and tested with real-world data. For example, Kangas et al. [20] tested an algorithm which used a logical AND to combine simple thresholds for peak acceleration towards the ground, impact magnitude and orientation relative to gravity. The algorithm was tested using a waist-worn accelerometer and achieved a sensitivity of 0.8 and precision of 0.03 in a test with fifteen falls recorded over a total 1,105 days from sixteen participants. It is the ratio of thirty-three false alarms for every fall detected which is the biggest issue and from the results of the current study is not unsurprising. It does not appear to be possible to separate eighty percent of falls based on peak acceleration towards the ground, impact magnitude and orientation without a comparatively large number of false alarms.

Bagala et al. [17] tested thirteen previously published algorithms using a set of twenty-nine falls and 1,170 sixty second non-fall periods extracted from 168 hours of accelerometer recordings using an activity detection algorithm. To collect the data, a lumbar-worn device was worn by nine participants with progressive supra-nuclear palsy and one community-dwelling older adult. All of the algorithms tested were based on thresholds for two or more of the following combined with a logical AND, impact magnitude, peak acceleration towards the ground, velocity and orientation. The performance of the algorithms was (mean ± SD) a sensitivity of 0.57 ± 0.27 and a precision of 0.19 ± 0.1, with the best performance being an algorithm which used all of the above features to achieve a sensitivity of 0.83 and a precision of 0.38. From the results of the current study, it would appear unlikely that markedly better performance could be achieved using these features and that the performance of the best algorithm is unlikely to be reproducible with the dataset used here.

Based on the results of this study, approximately twenty-five percent of falls cannot be distinguished from normal upright to sedentary transitions using the features tested, without exceptionally high rates of false positives (these were fall ID 3, 4, 14 and 23). This is because these falls had low acceleration towards the ground, vertical velocity, impact and orientation change and occupied the region of this feature space where there was the densest grouping of normal transitions (see: Figure 7.27). Only around fifty percent of falls occupy a space which is distinct, baring outliers, from the normal upright to sedentary transitions and could be detected with relatively high precision. The remaining twenty-five percent of falls occupy a space distinct from the densest area of normal upright to sedentary transitions, but which is still occupied by many more normal transitions than falls.

7.7.3 Implications for Future Research

There is a clear need to find new approaches if significant gains in fall detection performance are to be found. Lead-time (the time between the pre-impact nadir and the impact peak) is a feature which appears to have potential to reduce false positives due to the tight grouping of the falls, however, the majority of normal transitions have a low lead-time and occupy the same space as the falls. Therefore, the use of lead-time is unlikely to keep false positives to an acceptable level if a classifier was designed to detect the most troublesome falls, which based on current methods cannot be separated from normal transitions.

The prevailing approach to wearable fall detection could be characterised as based on a model of a falling object, which once falling continues until it strikes the ground. In contrast to an object, people can influence their motion through interaction with the floor, walls and surrounding objects such as furniture. People also have a natural reaction to try and stop themselves falling, or at least lessen the impact, which could include grabbing onto furniture, reaching for a wall to provide support or breaking the fall with their arm. These reactions could lead to a somewhat controlled descent and multiple relatively small impacts rather than one large one. The results of this study showed that almost seventy percent of falls had multiple impacts, compared to less than five percent of normal transitions and that there was overlap between falls and normal transitions for the features based on peak vertical motion and impact. Therefore, falls with multiple impacts, where the largest is no greater than those which occur in normal transitions, appear common.

Based on the findings of this study, it would appear that features which assess secondary and tertiary impacts have the potential to unlock fall detection performance which has previously been unattainable. In this study, the elementary approach of simply counting impacts was used to explore, for the first time, how the number of impacts differed between falls and normal transitions. The analysis showed that a count of peaks as a proxy for impacts could achieve a good separation ($\rho = 0.94$) between falls and normal transitions. Future studies could expand on this approach in several ways, for example, by improving the method of identifying impacts through analysis of the shape of the peak, by characterising the magnitude of all impacts or by characterising the motion before subsequent impacts in the same manner as has been done for the main impact. In addition, the direction of motion before impact could also be analysed to identify any difference between the small proportion of normal transitions with multiple impacts and falls.

Another potential area which could be further explored is the use of activity monitoring and posture classification to identify types of falls and the use of different classifiers for each type. This study is the first to use posture analysis to identify periods of interest for analysis as a potential fall. Previously studies have sliced their entire set of recordings into fixed-length windows and either used all the windows [e.g. 109] or used an activity detection algorithm to select windows [e.g. 114]. Upright to sedentary posture transitions were the focus of this study because this was the only activity class for which enough fall data were available; only four of the falls recorded were not from upright to sedentary and subdividing the sixteen upright to sedentary falls would have led to too few fall samples in each category and increase the risk that findings will not generalise. None of the features or pairs of features analysed were able to fully separate falls from the normal transitions, however, this has also been the case in all real-world fall detection research. It may be that grouping all upright to sedentary transitions together results in too broad a category, and further subdivision may be beneficial where enough data is available to facilitate this.

The grouping of upright to sedentary posture transitions encompasses transitions to sedentary from walking, from quiet standing and upon standing from a sedentary posture.

For each of these subgroups, there is the potential to extract features specific to the group. For example, in a transition from walking to sedentary the walking period could be analysed to identify signs of imbalance such as a dramatic change in cadence. Where there is a return to sedentary upon standing, the orientation of the thigh could be assessed before and after the attempt to stand to assess if there was a return to the original position (i.e. sitting back in a chair) or a new position (i.e. on the floor following a fall). By first identifying the type of transition, features can be extracted which are specific to the pre and post-fall activities, without this context one is limited to only generic features which make sense in any context. Where future studies have enough data to divide their dataset according to the context of the fall, it is recommended that this approach is used so that new context-specific features can be investigated. This approach of combining activity monitoring with fall detection could also allow each fall to be automatically classified by type, something which could be highly valuable in falls research.

The findings of this study primarily have implications for research into wearable fall detection, however, the knowledge gained on the mechanics of falls is also useful for non-wearable approaches. Given that there was substantial overlap between the falls and normal transitions for impact magnitude, approaches based on sensing vibration are unlikely to achieve a high level of performance. The results indicated that profiling vertical motion and change in orientation is not sufficient for reliable detection of falls without high rates of false positives. However, systems which can directly measure displacement, such as computer vision or Doppler radar, may find differences which cannot be detected with an accelerometer due to difficulty accurately estimating displacement. The approach of using activity monitoring to identify periods of interest and analysing pre posture transition activities could be applied to computer vision approaches to utilise the rich set of data these systems can collect.

7.7.4 Limitations

This study was limited by the small sample of falls, an issue which has been common in the majority of fall detection studies which have used real-world data (see Table 4.2). In the review of real-world fall detection studies (Chapter 4), the median number of falls used was 17.5 (IQR 8.25 to 29 falls), in line with the number of fall samples used in the current study. Where features were common, the findings agree with that of Bourke et al. [114], which is the only other study to analyse features rather than test fall detection technology.

The findings also fall in line with what would be expected based on the performance of fall detection technology which has used the features analysed here [e.g. 17,20]. This agreement with other studies gives reassurance that, despite the small sample of falls, the findings are valid and likely to generalise.

The limited range of the activPAL3 sensor of ±2 g and the low sample rate of twenty hertz were also both limiting factors. High impact magnitudes were missed due to the limited range in eleven of the falls, and even for lower magnitude falls the true peak may have occurred between samples and therefore been missed. Similarly, peak jerk may have been underestimated due to the limitations of the sensor preventing the shape of the peak to be accurately captured. These limitations are not unique to this study, Bourke et al. [114] also used the activPAL3 device to capture some of their data and therefore had the same limitations. Future studies should use a device which is capable of greater than ±2 g range and has a higher sample rate such as fifty hertz if this is achievable without reducing participant comfort due to a larger device or increasing inconvenience as a result of a need for frequent recharging.

7.7.5 Conclusion

This study was the first to analyse real-world fall signals recorded with a thigh-worn triaxial accelerometer and to integrate posture classification to identify periods of interest for analysis. The results showed that features which have been commonly used in previous wearable fall detection were not able to separate the falls from normal upright to sedentary posture transitions with acceptable precision. The analysis of secondary and tertiary impacts emerged as a promising area for further research as almost seventy percent of falls had multiple impacts compared to less than five percent of normal transitions. The use of posture classification as the first step in fall detection has greater potential than could be explored in this study due to the small sample of falls. Where enough data is available, future studies should consider further categorisation and extraction of features specific to the pre and post-transition activities such as analysis of steps during walking periods. The most promising areas for further research appear to be the characteristics of multiple impacts and the extraction of features specific to pre and post-fall activities.

Chapter 8

Summary, Recommendations and Conclusions

8.1 Summary

There are two areas where fall detection can contribute to the problem of falls: (1) as an alarm system and (2) in falls research to accurately track the occurrence of falls. Research has shown that when provided with a push-button alarm, over eighty percent of fallers do not activate their alarm even when they cannot get up without assistance (Section 2.3.1). The automatic detection of falls would remove the need for the faller to acknowledge the need for assistance and reduce the occurrence of long-lies and their associated consequences.

Accurate records of fall occurrence are vital in fall risk assessment and fall prevention research. The ability to detect falls would also remove the need for research to rely on self-report or reports by care staff, which are known to be unreliable, to track the occurrence of falls (Section 2.3.2). In addition, the technology used to automatically detect falls could also be used to gather information about the falls which occur as well as monitor activities and behaviours in the lead up to a fall. Such technology could revolutionise fall prevention research and lead to a reduction in the occurrence of serious falls.

The overarching aim of the research presented in this thesis was: to identify why existing wearable fall detection technology has not achieved acceptable performance and where further development should focus. The main aim was divided into the following five sub-aims: (1) to formulate a new framework for the development of fall detection technology, (2) to identify how fall detection performance should be quantified, (3) to test the activPAL3 device as an instrument to record fall signals, (4) to collect a real-world dataset of falls and activities of daily living comparable in size to the largest used in previous studies, and (5) to analyse real-world fall data in line with the proposed framework such that the main aim is achieved.

8.1.1 A Framework for the Development of Fall Detection

Chapter 3 presented a review of the literature on previous approaches to fall detection and based on the findings a new framework for the development of fall detection technology was proposed. The majority of research on fall detection had used simulated (acted) falls and ADL, however, the evidence showed that these were a poor substitute for real-world data. Where fall detection technology had been tested on both simulated and real-world data, the performance was substantially worse in the real-world. Hence, the conclusion that real-world data was needed to identify how performance could be improved beyond the current state-of-the-art.

The studies that had used real-world data had focused on testing performance (as had the majority of studies which used simulations); as a result, there was a lack of understanding as to how performance could be improved. Therefore, a new framework for iterative development of fall detection technology was proposed. The framework emphasised a feedback loop between each test of performance where the following research is carried out: (1) analysis to understand the detection errors which occurred, (2) development and testing of new feature extraction techniques, and (3) testing of how useful the new features are for fall detection. The critical component, which has been missing in the literature, is the study of how well features distinguish falls from ADL and how features interact. It is through such analysis that evidence is accumulated to steer the path of development and to support design decisions; without this research, one cannot hope to make efficient progress.

8.1.2 How Fall Detection Performance Should Be Quantified

Through a systematic review of the methods used to evaluate fall detection performance using real-world data (Chapter 4), the strengths and weakness of the various methods used previously were identified and a new approach was proposed. This was the first-ever study to look into how the performance of fall detection technology can be robustly assessed and several important issues were identified. For certain measures of performance commonly used, such as specificity and accuracy, there is a need for a count of true negatives which are segments of data that contain no fall signal and were correctly classified as not a fall. The main issue the review identified was a lack of consistency in how non-fall events were defined or identified and that the method used was likely to influence the results for measures of performance which rely upon true negatives more than the actual technology being tested. As a result, it was recommended that measures which rely on a true negative count be avoided and that sensitivity be used to assess the ability to detect falls, precision be used to assess the ability to avoid false alarms and F-measure be used as an overall measure to compare systems.

8.1.3 Suitability of the activPAL3 for Fall Detection Research

A pilot study was conducted (Chapter 5) to record posture and simulated fall data so that: (1) algorithms for the classification of posture before and after a fall could be developed and tested, and (2) the occurrence of clipping in signals recorded by an activPAL3 during a fall could be assessed. This was the first study to investigate if a thigh-worn accelerometer could be used to classify pre and post-fall posture. Data were recorded for common ADL, on-the-floor postures and simulated falls, all of which were conducted by young healthy adults. The developed algorithms could robustly distinguish upright and sedentary (sitting or lying) postures, but not sitting from lying. A threshold was devised which, the results showed, could identify lying flat on the front robustly; however, this was the only form of lying which could robustly be identified. When lying flat on the back, the orientation of the thigh is the same as sitting and this presents a substantial challenge for which there was no clear solution.

Rotation of the thigh about the longitudinal axis had been used previously to detect lying in bed [171]. This approach worked because people typically lie fully on their side at some point during a period of sleep. However, the same assumption could not be made for the moments which follow a fall, hence a more sensitive algorithm was developed. The results showed that to classify all of the recorded side-lying periods as lying required a threshold of just thirty degrees thigh rotation. It was deemed that such a threshold would result in substantial misclassification of sitting as lying in real-world use.

The analysis revealed that clipping occurred in the majority of the simulated fall recordings. The activPAL3 device was initially selected due to its small size, good battery life and because it had a proven track record in monitoring movement of older adults. While clipping of the signals was not desirable, on balance, it was deemed that the activPAL3 was a suitable device to record real-world fall and ADL signals. Due to continued advances in technology, the most suitable device continually changes. Therefore, future studies must reassess which device is most suitable for this work and should consider both wearable and non-wearable devices.

8.1.4 The Collection of a Real-World Dataset

Following the pilot study, a collaborative project with Four Seasons Health Care was launched to monitor care home residents using the activPAL3 and record a real-world dataset of falls and ADL (Chapter 6). The project ran for two years and a total of 1,919 days of recordings were collected with forty-two participants recruited from seventeen care homes. To establish which signal corresponded to the falls, two researchers independently analysed the signals in conjunction with the fall reports provided by the care homes. Where there was initial disagreement, a final decision was reached through collaboration. A total of thirty-two falls were reported during periods where accelerometer recordings were available. Twenty of the falls were identified in the accelerometer signals, four were deemed not valid, six occurred when the accelerometer was not worn and for two of the falls, no signal could be identified which matched the provided description.

The collected real-world fall dataset is one of the largest to date and represents a significant contribution to the field (see Table 4.2 for details of datasets used in previous studies). The only larger dataset collected with wearable sensors is a repository of 300 falls from the EU funded FARSEEING project which had substantially more resources, was a collaboration between six institutions and ran for four years, twice the duration of the data collection for this thesis. Eighty-nine falls did occur in the study by Lipsitz et al. [21], however, they tested a proprietary wearable fall alarm and the data were not stored, so analysis of the signals and tests of alternative classifiers are not possible. Twenty falls is a small sample and is not enough to both develop and test a robust fall detector, however, given the challenges in recording real-world falls the collection of a dataset of this size is a considerable accomplishment.

The main limiting factor in the size of the dataset was participant recruitment. Participant recruitment was carried out by the care staff in each of the homes involved; their priority was providing quality care and could only spend limited time on recruitment. Due to their existing relationship with the residents, care staff were best placed to carry out participant recruitment, especially where there were doubts over mental capacity. Therefore, the provision of funding to cover staff time spent on recruitment, in addition to their normal working hours, may be the most effective approach to increase participant numbers. Future studies should carefully consider the level of support required by any partner organisations involved in the recruitment of participants.

8.1.5 Insights into Why Previous Wearable Fall Detection Has Not Achieved Acceptable Performance and Where Further Development Should Focus

A comprehensive analysis of the real-world data was conducted to identify features of the signals which could be used to reliably detect falls (Chapter 7). A total of 4,277 normal upright to sedentary posture transitions were extracted and compared to the sixteen falls which were also transitions from an upright to a sedentary posture. The comparison consisted of eight features based on impact, vertical motion and orientation, four of which were the most commonly used in previous approaches to wearable fall detection. The study included a number of firsts in the field of real-world fall detection: it was the first to discern that falls may be too diverse to classify as a single group and focus on a single subtype of fall, it was the first to use posture transitions to select events for analysis, it was the first to assess the importance of vertical velocity at the point of impact for fall detection, it was the first to assess the importance of peak jerk for fall detection and it was the first to investigate the occurrence of multiple impacts during falls.

The results showed that the core features used in wearable fall detection (impact magnitude, peak acceleration towards the ground, vertical velocity and orientation change) do not yield sufficient separation of the falls to allow them to be detected without high rates of false positives. Peak jerk was found to give the greatest separation between falls and normal transitions of all the features tested. This finding indicates that a rapid increase in deceleration is more indicative of a fall than the peak deceleration. Peak jerk was also found to be highly correlated with impact magnitude; if future studies reproduce these findings then peak jerk should be used instead of impact magnitude. Combining both impact magnitude and peak jerk would provide little benefit to performance but would increase the complexity and the risk of over-fitting.

The analysis revealed that multiple impacts occur frequently in falls, but not in normal posture transitions. However, due to the rarity of falls, there were still almost ten times as many upright to sedentary posture transitions than falls with multiple impacts. There is, therefore, a need to find new features which can be used to distinguish between the falls and normal transitions where multiple impacts occur. Future research should investigate the extraction of features, similar to those used for the main impact and the preceding motion, from the secondary and tertiary impacts, where these occur. Since these impacts may be the result of lateral, rather than vertical, motion there is a need to develop methods to characterise any lateral motion which precedes an impact.

8.2 Recommendations for Further Research

The vast majority of published articles on wearable fall detection have simply tested some aspect of fall detection technology, primarily this has focussed on the classifier (software) [e.g. 17], but tests of complete systems have also been conducted [e.g. 21]. Through such tests, one learns only how that specific approach performs, yet very little can be learned from the results about why the performance was better or worse than other approaches. When looking at the field as a whole, the approach to fall detection could be characterised as trial and error. Given the lack of studies into how falls are unique, there is little evidence on which to base new approaches or to support adjustments to previous ones and these appear not to have been based on empirical evidence. Only through analysis such as that detailed in Chapter 7, can one gain insight into how performance can be improved.

There is a need for the focus of research to shift away from testing classifiers and to instead focus on feature generation, the process of identifying new features which are useful for classification. Therefore, future research should be planned in accordance with the framework proposed in Section 3.7, as was the case for the research presented in this thesis. The results presented in Chapter 7 showed that the main features used previously in wearable fall detection (impact magnitude, peak acceleration towards the ground, vertical velocity and orientation change) do not yield sufficient separation between falls and ADL. The analysis indicated that the current level of performance is likely to be the maximum possible through a combination of these features. Therefore, new features are needed to realise any substantial improvement in performance beyond the current state-of-the-art.

One new feature which should be explored further is impact count. The method used in Chapter 7 to count impacts was a basic peak height threshold arbitrarily set at 0.5 g. There is considerable scope for research into methods of identifying impacts and to assess if these produce a greater separation between falls and ADL. In addition, there is potential to research which characteristics of secondary and tertiary impacts, and of the motion which precedes them, are different between falls and ADL.

The use of activity monitoring algorithms in fall detection is another area where further research is worthwhile. The study presented in Chapter 7 was the first to use posture analysis as a method to identify potential falls. Due to having only a small sample of fall signals, only falls from upright to sedentary were investigated and this limited the analysis which could be conducted. Where larger samples are collected in future, studies should separately investigate falls from walking, falls from quiet standing and falls upon standing from a sedentary posture. Such separation would allow investigation of features specific to each pre-fall activity, this could include, for example, development of algorithms to characterise stability in standing up, in walking and changes in walking stability in the lead up to the transition to a sedentary posture.

The main limiting factor in the research for this thesis was the volume of real-world fall data collected; the small sample limited the scope of the analysis which could be conducted. It has long been established that the collection of real-world fall data is challenging due to their rarity and the lack of real-world data has been the main hindrance to progress in the field as a whole. One issue is that the collection of even a small sample of falls requires a large scale project and therefore a considerable investment. A potential approach to increase the return on this investment is to combine fall data collection with other activity monitoring studies. Where activity monitoring studies are conducted on those with a high fall risk there is the potential to additionally collect fall reports so that the data can be used for fall detection research. This approach of collecting fall reports as part of other studies is likely to be the most effective approach to collecting real-world fall data.

8.3 Conclusions

This thesis includes the first investigation of how fall detection research has been conducted. It was identified that the focus had been on testing complete systems rather than developing an understanding of which characteristics are unique to falls and building an evidence base to underpin new approaches. A new iterative framework was proposed which outlined the steps needed to ensure efficient progress on fall detection performance. This thesis also included the first look into how fall detection technology should be tested using real-world data. It was established that sensitivity and precision are the most informative measures of performance and the harmonic mean of these, F-measure, is the most suitable measure to compare approaches.

This thesis presented the most comprehensive analysis of real-world falls to have been conducted. The analysis demonstrated that rapid vertical motion and high impact magnitude are not unique to falls and not all falls exhibit these features. This finding is critical since the prevailing approach to wearable fall detection has been the identification of a single high magnitude impact, rapid vertical motion and change in orientation. It is now clear that while there is value in impact magnitude, vertical motion and change in orientation, they are not sufficient for high-performance fall detection.

For the first time falls were shown to commonly have multiple impacts but these were rare in normal posture transitions. Therefore, a count of impacts could improve fall detection performance. Additionally, characterisation of secondary and tertiary impacts warrants further investigation to identify any differences between the falls and ADL with multiple impacts.

This was the first research to explore the use of posture transitions to restrict the type of movement and was only limited to upright to sedentary transitions due to the small sample of falls. There is considerable scope to further investigate the use of posture and activity classification in fall detection. The extraction of features specific to the activity prior to a descent towards the ground and the characterisation of multiple impacts are the main areas where there is potential to find performance improvement beyond the current state-of-the-art.

These findings represent a significant contribution to the field of fall detection through (1) identifying the limitations in the way fall detection research has been conducted and proposing a new framework, (2) identifying the most informative measures of real-world fall detection performance, (3) furthering the understanding of how to detect falls, and (4) identifying promising areas for further research which had previously not been considered.

Appendices

A Overview of Fall Risk Assessment & Prevention

A.1 Fall Risk Assessment

In the UK, the guidelines indicate that a fall risk assessment should look for factors which may cause a fall such as gait, balance, mobility or muscle problems, home hazards, visual impairment and cardiovascular health [187]. The UK National Institute for Health and Care Excellence (NICE) advocate that persons with gait or balance abnormalities or who have fallen should be given a multifactorial risk assessment [187]. NICE recommend that assessments look at factors, such as osteoporosis, which may make injuries from a fall more severe. NICE also suggest assessments consider other factors which have been linked to falls, such as urinary incontinence, cognitive impairment, perceived functional ability and fear of falling.

A vast array of fall risk assessment tools have been reported in the literature, often these have only gone through limited testing and are therefore not ready for widespread adoption [188–190]. Most assessments fit into one of two categories, assessments of physical function or multifactorial assessments which encompass a range of factors [189]. Multifactorial assessments are most commonly used in LTC and hospital settings whereas assessments of physical function are most commonly used to assess community-dwelling older adults [188,191]. Multifactorial assessments can be further categorised as either comprehensive multidisciplinary assessments or screening tools, commonly either a questionnaire or form filled out by a nurse or general practitioner.

A.1.1 Comprehensive Multidisciplinary Assessments

Comprehensive multidisciplinary assessments comprise examination by a range of specialists and may form part of an overall geriatric assessment or be carried out as a standalone assessment following a fall [188]. The expert opinion of multiple specialists makes this the most rigorous form of assessment and most likely to identify suitable interventions. However, due to requiring multiple specialists to carry out detailed assessments, they are time-consuming, expensive and cannot be widely adopted [188]. Comprehensive multidisciplinary assessments can be very specific to the patient, however while flexibility may be good for the patient, it makes it challenging to assess their effectiveness. Although with multiple specialists making assessments these are likely to be effective.

A.1.2 Multifactorial Assessment Tools

Multifactorial assessment tools assess a set of factors known to be associated with fall risk such as cognitive function, mobility, medications and fall history [188,189]. Most of these tools are used in face-to-face meetings, however, some can be conducted over the phone or completed independently by the patient [189]. The complexity of assessments varies widely and they can take anywhere from a few minutes to over an hour to complete [188,189]. The more simple multifactorial tools solely use yes/no or multiple-choice questions and can, therefore, be scored easily, whereas more complex assessments include open questions, which can be subjective and require clinical expertise to interpret [188].

Wagner et al. [190] studied the fall risk assessment tools used in nursing homes and found a wide variety of approaches, the majority of which had not been validated. The findings of Wagner et al. [190] are perhaps unsurprising given the lack of clarity in the literature. Currently, it is challenging to determine which assessment tool is most appropriate for a given circumstance due to a limited evidence base. No multifactorial assessment tools have been shown to be accurate in multiple settings and therefore different tools should be used for assessments in the community, LTC and hospitals [189,191]. Many of these tools have only been through limited testing and where testing has been more extensive, results have been highly variable [189,191].

One of the most extensively tested tools is the St. Thomas's Risk Assessment Tool in Falling Elderly Inpatients (STRATIFY), which is commonly used in hospital settings [189]. STRATIFY provides a good illustration of the current performance of multifactoral assessment tools; its reported performance is broadly similar to that of other tools and it is one of the most tested [189,191,192]. The reported sensitivity and specificity of STRATIFY ranges from 0.66 to 0.93 and 0.34 to 0.68, respectively [191,193–200]. These sensitivity and specificity scores show that STRATIFY does not accurately classify fall risk. Indeed, when compared to the clinical judgement of nursing staff, STRATIFY has been found to be no more accurate [192,193].

A.1.3 Physical Function Assessment Tools

Physical function assessment tools focus on identifying physical limitations in mobility, gait and balance [188]. Since many physical limitations have been associated with fall risk (Section 2.2), a number of physical function assessment tools have been tested for this purpose. Physical function assessment tools vary widely in terms of complexity and the time required to complete them. Some of these tools assess physical function on a single task and may take only one minute to complete whereas others include multiple tasks and may take twenty minutes [188,189].

A commonly used and well-tested example of a quick and simple assessment of physical function is the Timed Up and Go test (TUG) [189,191]. TUG is recommended for routine screening by both the American Geriatric Society and the British Geriatric Society [201]. TUG measures the time taken to stand from a chair, walk three metres, turn around, return to the chair and sit down. In a recent meta-analysis, TUG was found to identify high fall risk persons with a sensitivity of 0.76 and specificity of 0.49 [191]. However, the reported performance of TUG varies widely between studies, sensitivity ranges from 0.67 to 0.83 and specificity ranges from 0.19 to 0.89 [191]. There is a large body of evidence which shows that TUG is a poor predictor of fall risk [191,202,203].

The Berg Balance Scale (BBS) is an example of a more comprehensive physical function assessment tool. BBS consists of fourteen balance-related tasks including variations of standing, sitting, transfers and turning [204]. A recent meta-analysis found BBS identified those at risk of falling with a sensitivity and specificity of 0.73 (range 0.50 to 0.92) and 0.90 (range 0.82 to 0.94), respectively [191]. It is clear that although more accurate than TUG, the BBS predicts fall risk with less than desirable accuracy. The reported performance of other physical function assessment tools is broadly similar to that of TUG and BBS and there are currently none which predict falls with a high degree of accuracy [188,189,191,205].

A.1.4 Fall Risk Assessment Summary

The evidence suggests that a team of clinicians can identify risk factors and suitable interventions, however, the cost of such assessments is likely to prevent their widespread adoption. By contrast, there is limited evidence to support less time-consuming assessment tools which could be carried out by a general practitioner or community nurse during a routine appointment. Current fall risk assessment tools provide insufficient accuracy and there is limited evidence to support their use over clinical judgement [189,191,193,206,207].

A.2 Fall Prevention

Evidence suggests that tailored interventions which address the individual risk factors are the best approach to prevent falls [28,208]. In the UK the National Institute for Health and Care Excellence (NICE) recommend strength and balance training combined with interventions to mitigate home hazards, visual impairments and the effects of medication [187]. The following sections provide an overview of the efficacy of these types of interventions.

A.2.1 Exercise Interventions

In community-dwelling groups exercise has been shown to significantly reduce the risk of falling [28,209]. Numerous studies have shown that exercise which contains strength and balance components reduces both the rate and risk of falls, independent of whether it was carried out in a group or at home [for reviews see 28,209]. Conversely, it is unclear if exercise interventions reduce the rate or risk of falls in care facilities or hospitals, due to insufficient quality evidence [208,209]. There is good evidence to support exercise interventions for those with cognitive impairment [209,210] and Parkinson's [209]. However, further research is needed on the effect of exercise on fall risk in other clinical groups [209].

A.2.2 Medication Adjustments and Dietary Supplements

For those on medications which are known to increase the risk of falling, gradual withdrawal has been shown to reduce the rate of falls for those in the community but not those in care facilities [28,208]. Within fall prevention research Vitamin D is the main supplement which has been tested [28,208]. The rationale is that Vitamin D supplementation may help maintain or improve muscle and bone strength [211]. However, the two latest Cochrane reviews found Vitamin D did not reduce the rate of falls or risk of falling, except where Vitamin D levels were low [28,208]. High levels of vitamin D supplementation may increase the risk of falls and is not recommended [212].

A.2.3 Hazard Assessment and Mitigation

Solutions to mitigate fall-related hazards can be put in place following an assessment. Hazard mitigation may, for example, include environmental adaptations or the provision of mobility aids. Such interventions have been shown to be particularly effective in those with high fall risk or visual impairment [28]. For those with very high fall risk due to poor mobility and cognitive impairment, chair and bed presence sensors can be used to alert care staff. However, evidence demonstrating their effectiveness in reducing falls is limited [208].

A.2.4 Fall Prevention Summary

Exercise-based interventions have the strongest evidence base, however, further research is needed to assess the efficacy in clinical settings [28,208,209]. The evidence to support fall prevention interventions is stronger in community-dwelling groups compared to clinical settings [28,208]. The quality of studies in clinical settings is low and no interventions have been shown to be highly effective [208]. More research is needed to identify effective interventions and which specific groups each intervention is most appropriate for.

B Pilot Study Ethical Approval

Research, Innovation and Academic Engagement Ethical Approval Panel

College of Health & Social Care
AD 101 Allerton Building
University of Salford
M6 6PU

T +44(0)161 295 7016
r.shuttleworth@salford.ac.uk

www.salford.ac.uk/

20 January 2015

Dear Malcolm and Robert,

RE: REQUEST TO AMEND ETHICS APPLICATION HSCR14/72 – Development of a novel thigh-worn detection monitor

Following your request submitted to the Panel on 15th January 2015 to amend this previously approved ethics application, based on the information you provided I am pleased to inform you that this has now been approved.

If there are any changes to the project and/ or its methodology, please inform the Panel as soon as possible.

Yours sincerely,

Rachel Shuttleworth

Rachel Shuttleworth
College Support Officer (R&I)

C Pilot Study Recruitment Documents

C.1 Pilot Study Recruitment Email

Email to healthy participants, Version 4 (15-01-2015)

“Research volunteers required to help develop a novel falls detection monitor”

Falls and their related injuries among older people are common and have serious impacts on the individual, their family, the health service and the economy. The focus for this proposal is the development of a novel wearable system for falls detection. This approach shows promise, but current systems are greatly limited by poor specificity, and/or the acceptability in the case of systems based on numerous sensors.

We are seeking healthy participants aged between 18-60, who would be willing to come to the human physiology lab (Mary Seacole, University of Salford) to simulate a range of on-the-floor postures, daily activities (such as sitting and walking) and falls. The falls will be simulated on a gymnastics mat. With the various posture and falls data we will be able to design a falls detection system which will be significantly more robust than what is currently available.
You will not be eligible to participate in this study if you:

- have had a previous fracture,
- have been diagnosed with osteoporosis
- have been diagnosed with any heart condition requiring medication

If you agree to take part in the study, you will be required to visit the human physiology laboratory at the University of Salford on one occasion. The total time for the visit is 1-1/2 hours. The visit will involve:

- Attachment of the thigh worn device
- Simulation of on-the-floor postures e.g lying on front/back
- Simulation of daily activities e.g walking, sitting
- Simulation of falls onto a gymnastics mat

Anyone interested in the taking part should email Robert Broadley at:
R.Broadley@edu.salford.ac.uk.

C.2 Pilot Study Participant Information Document

GMAHSN - Development of a novel fall detection monitor
Participant Information Document Version 3.4 (14-01-15)

INFORMATION ABOUT THIS DOCUMENT

You are being invited to take part in a research study to help us develop a new device which will detect falls. Before you decide, it is important for you to understand why the research is being done and what it will involve. This document gives you important information about the purpose, risks, and benefits of participating in the study. Please take time to read the following information carefully. If you have any questions then feel free to contact the researcher whose details are given at the end of the document. Take time to decide whether or not you wish to take part.

PROJECT TITLE:

DEVELOPMENT OF A NOVEL THIGH WORN FALL DETECTION MONITOR

BACKGROUND TO THE STUDY

Falls and their related injuries among older people are common and have serious impacts on the individual, their family, the health service and the economy. Around 40% of over the 65s living at home are estimated to fall at least once a year and both the incidence of falls and the severity of the consequences increases rapidly with age. In clinical practice there are three main types of fall detection systems, video-based, novel approaches to instrumenting flooring, and systems based on wearable movement sensors. Video-based approaches raise ethical issues and clearly cannot be used outside of the house/care home. Instrumenting flooring approaches are early in their development. The focus for this proposal is the development of a novel wearable system for falls detection. This approach shows promise, but current systems are greatly limited by poor specificity, and/or the acceptability in the case of systems based on numerous sensors.

The proposed novel solution is that by classifying body postures, from an accelerometer based device attached to the thigh, one would be able to robustly detect that a fall has occurred. A fall would be characterised by a change from a normal body posture to an unexpected body posture.

WHAT WILL HAPPEN TO ME IF I PARTICIPATE IN THIS STUDY?

How long will it take?

If you agree to take part in the study, you will be required to visit the human performance laboratory at Salford University on one occasion. The total time for each visit is 1.5 hours.

What will you do?

1. Consent and medical screening.
2. After informed consent has been taken, the thigh-worn device will be attached to the anterior aspect of the thigh with a hydrogel pad (PAL Technologies Ltd. Glasgow, UK).

1

3. You will then be asked to simulate a number of on-floor-postures which represent the posture a person may find themselves in after a fall. This will be completed on a mat and the investigator will provide guidance. You will be filmed while simulating these postures so there is a record of your body position which can be used to check the data from the thigh-worn device. These postures will be:
    a. Lying on front
    b. Lying on back with legs straight
    c. Lying on back with knees up
    d. Lying on both sides
    e. Hands and knees
4. In between each of the on-floor-postures data will be collected for a number of everyday activities such as walking. These are needed for the device to distinguish between a fall posture and normal everyday tasks.
5. You will then be asked to simulate a number of falls. These are needed to test the accuracy of fall detection. The falls will be simulated onto gymnastics mats. You will be filmed while simulating these falls so there is a record of your body motion which can be used to check the data from the thigh-worn device. Example falls are:
    a. Fall from standing (simulating a faint)
    b. Fall from standing (simulating a trip or loss of balance)
    c. Fall while walking (simulating a faint)
    d. Fall while walking (simulating a trip or loss of balance)

Am I able to participate?

To participate you need to be age 18 years or older and must not:

- Currently take medication that might affect your ability to participate in the research as outlined.
- Have been advised by your doctor that you should only do physical activity recommended by a doctor.
- Currently be receiving treatment from a doctor or other medical professional (e.g. physiotherapist).
- Suffer from any of the following (or similar): diabetes, epilepsy, seizures, osteoporosis, arthritis, any cardiovascular or respiratory disorder.
- Currently suffer from a musculoskeletal injuries e.g. ankle sprain/strain, tendonitis, etc.
- Have recently suffered a bone fracture (within the previous 24 months).
- Have previously suffered a concussion or other head injury.
- Currently be pregnant or have recently given birth (within 3 months).

RISKS & POTENTIAL BENEFITS OF THE STUDY

What risks are involved in participating in the study?

This is a very simple, straight forward study with negligible risks. The simulation of falls has been completed in a number of previous studies using the same method.

If I participate in this study, can I also participate in other studies?

As the testing for the project only requires one visit and there is no on-going treatment or assessment taking part should not affect any other studies that you are involved in. However, if you are already taking part in other research, or would like to do so, please discuss this with the researcher (Robert Broadley).

What benefits are involved in participating in the study?

You will not benefit directly from taking part in the study. However, the results will improve the current fall detection device. By reducing false positives there would be an increased reliance on a fall detection system by caregivers. For patient care the main aspect of being able to detect a fall reliably would give the wearer the confidence that in the event of a fall an appropriate response will be made.

What if something goes wrong?

The university has insurance to cover against harm to you which may occur whilst you are taking part in these tests. However, if you decide to take legal action, you may have to pay for this. If you wish to complain, or have any concerns about any aspect of the way you have been approached or treated during the course of this study, you can approach the University of Salford. Previous studies using this procedure have not reported any injuries.

ENDING THE STUDY

What if I want to leave the study early?

You can withdraw from this study at any time without loss of any non-study related benefits to which you would have been entitled before participating in the study. There is no danger to you if you leave the study early. If you want to withdraw you may do so by notifying the study representative listed in the "Contact Information" section below.

FINANCIAL INFORMATION

Who is organizing and funding the research?

The Greater Manchester Academic Health Science Network is funding this research. www.gmahsn.org/

University of Salford MANCHESTER

GMAHSN - Development of a novel fall detection monitor
Participant Information Document Version 3.4 (14-01-15)

Will I be paid for participating?

Unfortunately financial reward will not come from taking part in this research. However, you will be participating in a study with a novel idea and it could have a positive impact on the care of the elderly.

CONFIDENTIALITY OF SUBJECT RECORDS

Will my taking part in this study be kept confidential?

All information which is collected about you during the course of the research will be kept strictly confidential. Any information about you which leaves the University of Salford will have your name and address and any other identifying features removed so that you cannot be recognized from it.

What will happen to the results of the research study?

A summary of the research findings will be sent to everyone who participates in the experiments. Significant findings may be published in clinical and engineering journals.

CONTACT INFORMATION

If you require more information about the study, want to participate, or if you are already participating and want to withdraw, please contact:

Robert Broadley
Email: R.Broadley@edu.salford.ac.uk
Address: School of Health Sciences
Brian Blatchford Building,
University of Salford,
Frederick Rd Campus,
Salford, M6 6PU.

RECORD OF INFORMATION PROVIDED

Your will receive a copy of the information sheet and a signed consent form to keep for your personal records.

Thank you very much for taking time to read this document!

We appreciate your interest in this study and hope to welcome you at the School of Health Sciences, University of Salford.

C.3 Pilot Study Consent Form

University of Salford MANCHESTER

GMAHSN - Development of a novel fall detection monitor
Consent form Version 3.1 (14-01-15)

Study Number: HSCR14/72
Participant Identification Number:

CONSENT FORM

Title of Project:
GMAHSN - Development of a novel fall detection monitor

Name of Researcher:
Robert Broadley, PhD Student, School of Healthy Science, University of Salford, Salford, M6 6PU.

(Delete as appropriate)

1.	I confirm that I have read and understood the **Participant Information Sheet** for the above study and have had the opportunity to ask questions.	Yes	No
2.	I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without my medical care or legal rights being affected.	Yes	No
3.	I agree to video footage being taken during the research exercises.	Yes	No
4.	I understand that the data collected during the study, may be looked at by named researchers from the University of Salford. These individuals will be Professor M Granat, Professor L Kenney, Dr S Thies, Dr S Preece and R Broadley. I give permission for these individuals to have access to my records.	Yes	No
5.	I agree to take part in the above study.	Yes	No

Page 1of 2

University of Salford MANCHESTER

GMAHSN - Development of a novel fall detection monitor
Consent form Version 3.1 (14-01-15)

For your own safety you must not take part in this research if any of the following are true:

- You are currently taking medication that might affect your ability to participate in the research as outlined
- Your doctor has advised that you should only do physical activity recommended by a doctor
- You are currently receiving treatment from a doctor or other medical professional (e.g. physiotherapist)
- You suffer from any of the following (or similar): diabetes, epilepsy, seizures, osteoporosis, arthritis, any cardiovascular or respiratory disorder
- You have recently suffered a bone fracture (within the previous 24 months)
- You are currently suffering from a musculoskeletal injuries e.g. ankle sprain/strain, tendonitis, etc.
- You have previously suffered a concussion or other head injury
- These is potential that you may be pregnant or have recently given birth (within 3 months)
- You are currently feeling unwell

6. I confirm that none of the above statements are true and am not aware of any other reason why I should not participate in this research as outlined. Yes No

Name of participant: ……………………………………………………………………………

Signature: ……………………………………………………………………………

Date: ……………………………….

Name of researcher taking consent: ………………………………………………………….

Researcher's e-mail address: ………………………………………………………….

D Real-World Study Ethical Approval

University of Salford
MANCHESTER

Research, Innovation and Academic Engagement Ethical Approval Panel

Research Centres Support Team
G0.3 Joule House
University of Salford
M5 4WT

T +44(0)161 295 2280

www.salford.ac.uk/

3 March 2016

Dear Chris,

RE: ETHICS APPLICATION HSCR 15-109 – A Novel body-worn falls detection system: development and evaluation in an older care home population

Based on the information you provided, I am pleased to inform you that your request to amend application HSCR15-109 has been approved.

If there are any changes to the project and/ or its methodology, please inform the Panel as soon as possible by contacting Health-ResearchEthics@salford.ac.uk

Yours sincerely,

Sue McAndrew
Chair of the Research Ethics Panel

NHS
Health Research Authority

Social Care REC
Ground Floor
Skipton House
80 London Road
London
SE1 6LH

Telephone: 0207 972 2568

06 June 2017

Prof Malcolm Granat
Professor of Health and Rehabilitation Sciences
University of Salford
P028a, Brian Blatchford Building
University of Salford
Manchester
M5 4WT

Dear Professor Granat

Study title:	**A novel body-worn falls monitor system: development and evaluation in the frail elderly population**
REC reference:	**17/IEC08/0019**
Protocol number:	**N/A**
IRAS project ID:	**225139**

Thank you for your letter of 20 March and 23 May 2017, responding to the Committee's request for further information on the above research and submitting revised documentation.

The further information has been considered on behalf of the Committee by the Chair.

We plan to publish your research summary wording for the above study on the HRA website, together with your contact details. Publication will be no earlier than three months from the date of this opinion letter. Should you wish to provide a substitute contact point, require further information, or wish to make a request to postpone publication, please contact hra.studyregistration@nhs.net outlining the reasons for your request.

Confirmation of ethical opinion

On behalf of the Committee, I am pleased to confirm a favourable ethical opinion for the above research on the basis described in the application form, protocol and supporting documentation as revised subject to the conditions specified below.

Mental Capacity Act 2005

I confirm that the committee has approved this research project for the purposes of the Mental Capacity Act 2005. The committee is satisfied that the requirements of section 31 of the Act will

E Real-World Fall Data Collection Documents

E.1 Project Overview

University of Salford MANCHESTER

Four Seasons HEALTH CARE

00 – Peel Trust Falls Project

Introduction

Falls are one of the serious and common health related problems amongst the older adult population. Over 40,000 falls have been recorded in the past year in Four Seasons Health Care homes alone. 'Long lies' or inability to get up following a fall has a greater adverse risk to an individual causing pressure sores, carpet burns, dehydration, hypothermia, and even death. Therefore, accurate detection of falls and immediate help would greatly minimise the adversities following a fall. However, current fall detection systems suffer from a high rate of false alarms. We aim to develop a new approach that minimises the false alarms.

We are currently running a research project as a collaboration between the University of Salford and Four Seasons Health Care. The project aims to collect data from 250 participants, each wearing a small movement monitoring device on their thigh for two months, during which we anticipate a number of falls will be recorded. We will use this data to research and develop new fall detection systems.

This document outlines the two major components of the project: 1. recruiting residents for the study and 2. collecting the data. The following documents (included in this pack) are needed for recruitment (documents 01 – 05 and video 01) and during data collection (documents 06 and 07). The purpose of each document and when they are required is explained in the sections that follow.

01.	Staff Information
02a.	Participant Information
02b.	Consultee Information
03.	Formal Assessment of Mental Capacity
04.	Resident Best Interests Assessment
05a.	Participant Consent Form
05b.	Consultee Declaration Form
06.	Device Monitoring Sheet
07.	Device Comfort Form
Appendix01.	activPAL Monitor Information
Video01.	Training on mental capacity (https://youtu.be/2BV6KjofPhg)

1. Resident Recruitment

Approval has been granted and a pathway developed to recruit residents with or without the capacity to understand the study and what is required to participate. Where residents cannot themselves understand the study and therefore cannot provide informed consent, a consultee must be identified who can provide informed assent on the resident's behalf.

Page 4 shows a flow diagram which outlines the pathway.

University of Salford MANCHESTER

Four Seasons HEALTH CARE

1.1 Who should be recruited?

FSHC management will work with the University to identify residents suitable to participate in the study. Homes will be provided with this list of residents and asked to recruit only the residents listed. It is important to remember the residents do not have to take part, however they or their consultee must be provided with all the information necessary to make a decision. Wherever possible the recruitment pathway for residents should be completed within seven days and the outcome sent to the nominated link person (details can be found at the end of this document).

1.2 Reason to Doubt Mental Capacity?

The first step is to identify a member of staff who knows the resident well enough to be able to make a decision on whether the resident could understand the study. The identified member of staff should be given document 01 – staff information to aid them in making the decision. Document 01 describes why the research is being done and what it will involve, it is very similar to the information which will be given to the resident or their consultee. Appendix 01 in the document pack contains images and extra information about the activPAL monitor, this may be useful to understand what is asked of residents.

The outcome of this decision should be recorded on the list of residents provided.

1.3 No Reason to Doubt Mental Capacity (Path A)

If there is no reason to doubt the resident's capacity to make a decision then give the resident a copy of document 02a – resident information. Document 02a describes why the research is being done and what it will involve. The resident should be given time to read the information and encouraged to ask any questions. Any questions staff cannot answer should be passed on to the University of Salford using the contact details provided at the end of this document. If needed, staff should explain the study in simple language to help the resident understand what is involved. Appendix 01 in the document pack contains images and extra information about the activPAL monitor, this should be used if residents ask questions about the monitor.

If the resident wishes to take part they should complete document 05a – resident consent form, which must be witnessed and signed by a member of staff. Please take the time to ensure document 05a is fully completed as this is a critical document. If the resident provides informed consent there will be approximately one week before data collection starts.

Whether the resident provides consent or not should be recorded on the provided list of residents. If the resident provides informed consent a copy of the completed consent form (document 5a) should be sent to the project link person (contact details can be found at the end of this document).

1.4 Reason to Doubt Mental Capacity (Path B)

If there is reason to doubt mental capacity a consultee must be identified. A consultee is someone who knows the resident well and is willing and able to offer an opinion as to what that resident's wishes would have been if they were able to make the decision. Please ensure records are checked to identify if a consultee has previously been nominated. The consultee could be the resident's partner, other relative, friend or member of their care team (care home staff, GP or other health professional).

Once the consultee has been identified they should be provided with a copy and given time to read document 02b – consultee information. Document 02b provides information about what the research involves and why it is being carried out. Appendix 01 in the document pack contains images and extra information about the activPAL monitor, this should be used if the consultee wants to know more about the monitor. If the consultee is interested in the resident taking part document 03 – formal assessment of capacity should be completed by a member of trained staff with support from the consultee. A training video for the assessment of capacity has been made available at: https://youtu.be/2BV6KjofPhg. Please ensure appropriate staff receive this training prior to approaching the consultee. The outcome of the capacity assessment should be recorded on the provided list of residents.

If the resident is found to have the mental capacity to make the decision for themselves then the steps detailed above in the section “1.3 No Reason to Doubt Mental Capacity (Path A)” should be followed.

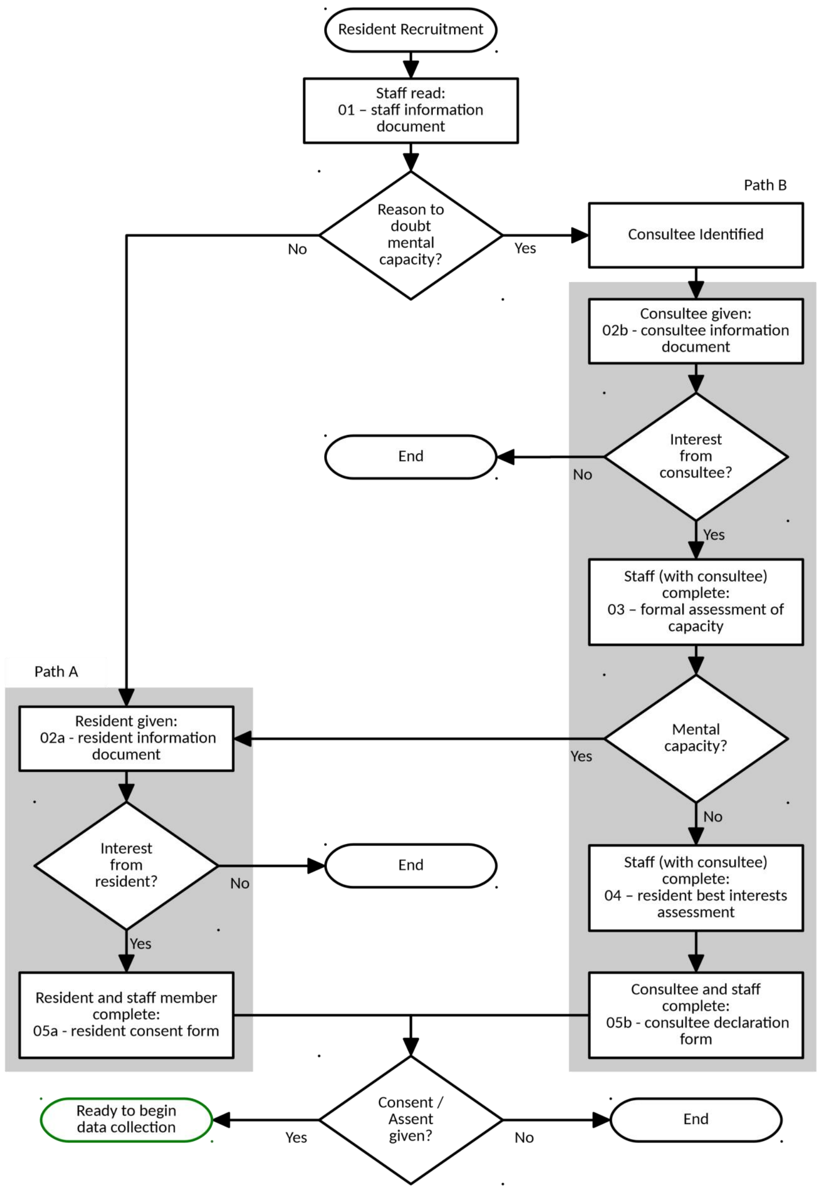
If the resident is found to not have the metal capacity to make the decision then document 04 – resident's best interest assessment should be completed by a trained staff member with support from the consultee. Training on completing document 04 is included in video 01 which is available at: https://youtu.be/2BV6KjofPhg. The same member of staff who completed document 03 formal assessment of capacity should also complete document 04 - resident's best interest assessment.

The outcome of the resident's best interest assessment should be recorded on the provided list of residents. If it is agreed that taking part would be in the interests of the resident then the consultee and a staff member should complete document 05b – consultee declaration. Please take the time to ensure document 05b is fully completed as this is a critical document. If the consultee provides informed assent there will be approximately one week before data collection starts.

Whether or not the consultee provides informed assent should be recorded on the provided list of residents. If assent is given a copy of the completed declaration form (document 5a) should be sent to the project link person (contact details can be found at the end of this document).

University of Salford MANCHESTER

Four Seasons HEALTH CARE



00 – Peel Trust Project Overview Version: 2017-11-20 4

2. Data Collection

Each time a new home starts participating in the study a member of the team from Salford University will visit the home to explain the project and provide staff training. Staff will be trained in where and how to attach and remove the monitor as well as how to manage a resident's involvement in the study. At the initial visit, all new participants will have a monitor attached to begin data collection. After the initial visit monitors will be sent by post with a preaddressed return envelope.

Where new residents are recruited from a home which has already been participating, the University will liaise with the home to determine if further staff training is needed.

Each monitor can record for up to 10 days before it requires recharging and reprogramming. After each 10-day recording period monitors should be returned to Salford University using the provided preaddressed envelopes. Upon receipt, staff at Salford University will send new monitors and consumables (Inc. preaddressed return envelope) to continue data collection.

2.1 Monitor Usage Recording

Every time the monitor is removed (for any reason) this should be recorded on the device monitoring sheet (document 06). It is more important to accurately record attaching or removing than it is to try and keep the device on the leg all the time. Device monitoring sheets should be returned to Salford University with each monitor and a new monitoring sheet will be sent with the replacement monitor.

2.2 When to Remove the Monitor

The monitor should be checked every 2 days to ensure it is still in place and the dressing is not coming loose.

The medical dressing used to secure the monitor should be changed after 5 days (halfway through the 10 day recording period). When the dressing is changed, the monitor should be moved to the other leg if possible, and this must be recorded on the device monitoring sheet.

If the participant is bathing (the thigh / monitor will be submersed in water) the monitor should be removed to prevent water damage. The devices are encased in a waterproof sleeve which allows showering without removing the monitor.

If the resident needs to attend hospital or a medical appointment outside the home the monitor should be removed, if possible, and reattached upon their return, if this is within the 10 day recording period. Hospitals have previously discarded the monitors as they do not know what they are.

2.3 Device Comfort Recording

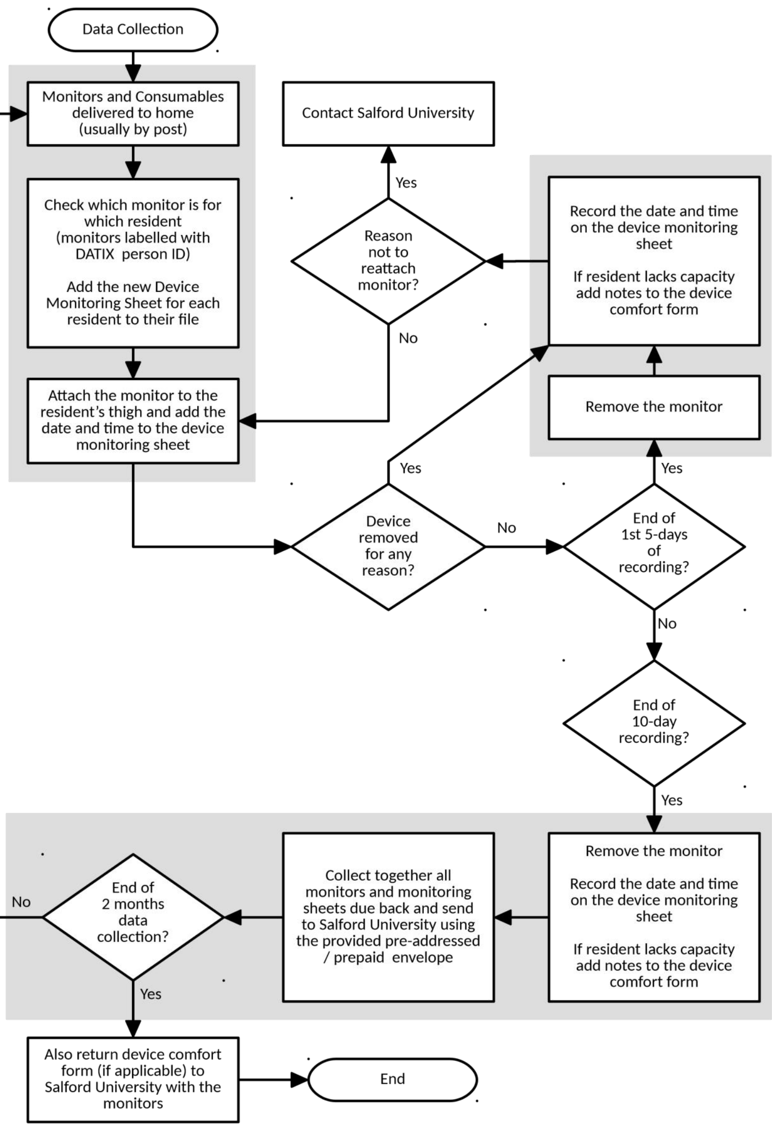
For participants who do not have capacity to consent to take part in the study the device comfort form (document 07) must be completed at least weekly to ensure that taking part in the study is not causing discomfort. It is preferred to complete the device comfort form when the dressing is changed after 5 days and when the monitor is removed to be returned to the university. If the participant shows signs of discomfort due to taking part in the study at any other time this should also be recorded. Any signs of discomfort should be reported to Salford University as soon as possible and if discomfort is serious participation should be temporarily withdrawn, pending advice from the University.

2.4 Fall Recording

All falls should be recorded on DATIX as usual. Without this, the information recorded on the monitoring device will be useless. Where possible, the direction in which the resident fell (e.g. forwards, backwards, to the side) and the position in which they were found should be recorded on DATIX.

2.5 Participant Withdrawal

Any participant who wants to withdraw can do so at any time. They do not need to give a reason. No "approval" is required from the study organisers. If a resident wishes to leave the study a note should be made in the care plan, the Home Manager and Salford University should be informed by email or telephone.


Data Collection
Monitors and Consumables delivered to home (usually by post)
Check which monitor is for which resident (monitors labelled with DATIX person ID)
Add the new Device Monitoring Sheet for each resident to their file
Attach the monitor to the resident's thigh and add the date and time to the device monitoring sheet
Contact Salford University
Yes
Reason not to reattach monitor?
No
Record the date and time on the device monitoring sheet
If resident lacks capacity add notes to the device comfort form
Remove the monitor
Yes
Yes
Device removed for any reason?
No
End of 1st 5-days of recording?
No
End of 10-day recording?
Yes
Remove the monitor
Record the date and time on the device monitoring sheet
If resident lacks capacity add notes to the device comfort form
Collect together all monitors and monitoring sheets due back and send to Salford University using the provided pre-addressed / prepaid envelope
No
End of 2 months data collection?
Yes
Also return device comfort form (if applicable) to Salford University with the monitors
End

E.2 Study Information Document

The participant information document is used as an example, versions with altered wording and adapted introdcutions were provided to care staff and consultees.

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Four Seasons HEALTH CARE

02a – Participant Information

"Research volunteers required to help develop a novel falls detection monitor"

Falls and their related injuries among older people are common and have serious impacts on the individual, their family, the health service and the economy. This study is to develop a wearable fall detector device that is simple to attach, discrete (worn on the thigh) and low maintenance for the user. The fall detector is just one device that is attached to the thigh, which is different to a lot of other fall detectors, which can use many devices at once. The monitor being developed aims to detect falls with a very low false alarm rate (when no fall has occurred) making it more useful than current devices on the market.

We are seeking participants who would be willing to wear a commercially available activity monitor for a period of 2 months. Participants must be residents within a Four Seasons Care Home.

To participate:

- You must NOT have an existing skin condition such as psoriasis or eczema that would be affected by the application of a medical and medical grade dressing.
- You MUST live in a Four Seasons Care Home
- You must NOT be wheelchair bound at all times

If you agree to take part in the study, you will be required to wear an activPAL activity monitor on the front of your thigh for a period of 7 days at a time before swapping to the other thigh. This will continue for 2 months. The monitor will be applied, removed and monitored by Four Seasons staff. No additional actions are required by the participants.

If you are interested in taking part, then please speak to the Home Manager at the home where you live.

02a – Participant Invitation Letter IRAS ID 225139 2017-11-20 v2.0

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Four Seasons HEALTH CARE

02a – Participant Information Sheet

Peel Trust Falls Project with Salford University

Dear Resident,
You are being invited to take part in a research study to help Four Seasons Health Care and the University of Salford develop a new device which will detect falls.

Before you decide, it is important for you to understand why the research is being done and what it will involve.

This document gives you important information about the purpose, risks, and benefits of participating in the study. Please take time to read the following information carefully.

If you have any questions then feel free to contact the Home Manager in the home where you live or Robert Broadley, the researcher whose details are given at the end of the document.

Please take the necessary time to decide whether or not you wish to take part.

Project Title:

'A novel body-worn falls detection system: development and evaluation in the frail elderly population'

Background to the Study

Falls and their related injuries among older people are common and have serious impact on the individual, their family, the health service and the economy. Over 40,000 falls have been recorded in the past year in the Four Seasons Health Care homes alone. 'Long lies' or inability to get up following a fall has a greater adverse risk to an individual causing pressure sores, carpet burns, dehydration, hypothermia, and even death. Therefore, accurate detection of falls and immediate help would greatly minimise the adversities following a fall. However, current fall detection systems suffer from a high rate of false alarms. We aim to minimise the falls alarms by robustly detecting an unexpected change (such as walking to lying) in body postures using body worn wearable sensors. Hence a fall would be characterised by a change from a normal body posture to one that is unexpected.

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Four Seasons HEALTH CARE

What will happen to me if I participate in this study?

How long will it take?
If you agree to participate in the study, you will be required to wear a thigh worn activity monitor for a period of **2 months/8 weeks** whilst continuing your normal routine.

What will you do?

1. Sign a consent form and take part in a medical screening.
2. After informed consent has been taken, the thigh-worn device will be attached to the front of the thigh with a medical dressing.
3. You **continue with your normal daily activity,** leaving the activity monitor in place.
4. The activity monitor will be swapped between your right and left thigh weekly for a period of 2 months. This will be carried out by a trained member of Four Seasons Health Care staff.
5. Please be aware that **this study does not increase or decrease your risk of falling, as we are only observing your physical behaviour over a given period of time.** However, if you do happen to experience a fall during that time, you (together with your family or carer support) will be asked to let us know - to the best of your knowledge - the circumstances under which the fall occurred.
6. You may also be asked to take part in an interview which is aimed at understanding long-term wear and methods of attachment (you may take part in the study but decline to be interviewed).

Am I able to participate?
To participate:

- You must **NOT have skin breakdown or an existing skin condition** (such as psoriasis or eczema) that would be affected by the application of a medical dressing of a medical grade adhesive dressing.
- You should be able to walk and must not be totally dependent on a wheelchair.

Risks & Potential Benefits of the Study

What risks are involved in participating in the study?
This is a very simple study with **no risks to you**. Some participants may experience some mild skin irritation from the hydrogel Stickie Pads and / or medical grade dressing used to attach the monitor. To minimise this, we recommend changing the medical dressing every two days. The activity monitor will be swapped to the other thigh every 7 days to further minimise any potential irritation. The activPal monitor has been used for many years in a number of studies involving 1000s of users, so the risks are minimal.

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Four Seasons HEALTH CARE

If I participate in this study, can I also participate in other studies?
As the testing for the project requires continuous use for 2 months, some other additional studies may interfere with data collection. If, however you are already taking part in other research, or would like to do so, please discuss this with the researcher (Robert Broadley).

What benefits are involved in participating in the study?
You will not benefit directly from taking part in the study. However, longer-term the data we will collect during the observation period will improve our knowledge regarding the design of fall detection devices. For example, by reducing false positives the uptake of fall detection systems by caregivers may increase, subsequently improving medical care for older adults. For the individual wearing a fall detection device, the main aspect of being able to detect a fall reliably would give them the confidence that in the event of a fall an appropriate response will be made.

What if something goes wrong?
If you are harmed by taking part in this research project, you are covered by the University's Public Liability and Professional Indemnity insurance policies (http://www.salford.ac.uk/finance/procurement).

In case of a complaint you can contact Anish Kurien (Research Centres Manager), Joule House G.08, University of Salford, M5 4WT (Phone: 0161 295 5276 / Email a.kurien@salford.ac.uk), or the Home Manager who will contact the university on your behalf.

Ending the Study

What if I want to leave the study early?
You can withdraw from this study at any time without loss of any non-study related benefits to which you would have been entitled before participating in the study. There is no danger to you if you leave the study early. If you want to withdraw you may do so by notifying the Home Manager who will then contact the study representative listed in the "Contact Information" section below.

Financial Information

Who is organizing and funding the research?
The Dowager Countess Eleanor Peel Trust is funding this research.

Will I be paid for participating?
Unfortunately, financial reward will not come from taking part in this research. However, you will be participating in a study with a novel idea and it could have a positive impact on the care of older adults like yourself.

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Confidentiality of Participant Records

Will my taking part in this study be kept confidential?
Yes. We take great care to protect the confidentiality of the information we are given, and we take careful steps to ensure that data is secure at all times. The information collected is used for research and statistical purposes only and is dealt with according to the 1998 Data Protection Act.

How will my data be used?
Anonymised research data will be archived in the University of Salford data repository. Information from this study will be made available for future research studies; however, no information collected and recorded can be used to identify individuals in the dataset.

What will happen to the results of the research study?
A summary of the research findings will be sent to the participating care homes. Significant findings may be published in clinical and engineering journals.

Contact Information

If you require more information about the study, want your friend or relative to participate, or if your friend or relative is already participating and want to withdraw, please contact:

Robert Broadley
Email: r.broadley@edu.salford.ac.uk
Address: School of Health Sciences
University of Salford,
Salford, M5 4WT
Phone: 0161 295 2507

Record of Information Provided

Your will receive a copy of the information sheet and a signed consent form to keep for your personal records.

Thank you very much for taking time to read this document. We appreciate your interest in this study.

E.3 activPAL Monitor Information

The activPAL monitor information sheet was produced to provide a simple overview of the device and how it is worn. It supplemented the main information documents and aided care staff in explaining the study to potential participants, especially those with a cognitive imparment.

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Four Seasons HEALTH CARE

activPAL™ Monitor Information

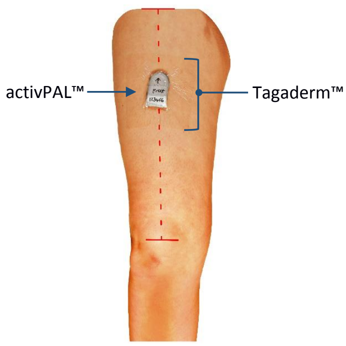
The Monitor

To collect data, we use the activPAL™ Micro monitor (shown below) which records movement and body posture in an unobtrusive way. The monitor is small and light, weighing only 10g or ⅓oz. It can record continuously for 10 days, after which the monitor must be sent back to Salford University so the data can be downloaded and the monitor recharged and reprogramed.

How It's Worn

The activPAL™ monitor is designed to be worn on the front of the thigh. It is attached using a 10cm square medical dressing called Tegaderm™. The dressing is thin and breathable; it should be comfortable and not restrict movement.

To provide resistance to water, the monitor is covered by a nitrile sleeve before it is attached to the thigh. The combination of the nitrile sleeve and Tegaderm™ dressing allow the wearer to shower while wearing the device, however it must not be submersed e.g. during swimming or a bath.



E.4 Assessment of Capacity Form

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Four Seasons HEALTH CARE

03 – RECORD OF FORMAL ASSESSMENT OF CAPACITY

Principle 1 of the Mental Capacity Act is the 'presumption of capacity'. This means that we should assume that people have the ability to make choices and decisions for themselves. However, where doubt exists, capacity should be formally assessed- see policy for details.

Personal Details of Individual for Whom Capacity is Being Assessed	
First name	
Surname	
Date of birth	
Gender	
Religion	
Ethnicity	

Details of Decision to be Made	
What is the decision to be made/why is capacity being assessed?	Use of device that will collect data for research to aid in the detection and prediction of falls. The small device is designed to be fitted to the front of the thigh.
Date of assessment	
Who requires the decision?	Care home staff and research team (Salford University)
Is there a timescale within which the decision must be made and if so, why?	
What are the options that exist?	There are no current alternatives to this device that will collect the specific data required to detect and predict (and therefore help prevent) falls.

Questioning Capacity
Bearing in mind the first principle of the Act- the assumption of capacity i.e. the assumption that people have the ability to make their own decisions - **what is the basis for questioning this individual's capacity to make this decision?**
(Explain what the specific decision that has to be made is and why capacity has to be assessed. The type of information here might include; the pattern to the person's falls or them appearing not to understand that their behaviour is increasing the risk of them falling e.g. Someone may have lost the physical ability to stand or walk but may not appear to fully comprehend this, thus forming the basis for questioning their capacity to make the decision regarding wearing the device to gather the data that may help to define certain conditions that increase the risk of a fall occurring.)

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Test of Capacity		
Does the person have an impairment of, or a disturbance in the functioning of the mind or brain? *Examples may include; conditions associated with some forms of mental illness; long term effects of brain damage; dementia; concussion; symptoms of drug or alcohol abuse*	Yes **Continue rest of assessment**	No **The person does not lack capacity under the MCA**
Does the impairment or disturbance mean that the person is unable to make a specific decision when they need to?	Yes **Evidence details of assessment below**	No **The person does not lack capacity under the MCA**
Does the person have capacity to make this decision at the time it needs to be made?	Yes	No

Evidence for Findings - Understanding Information Relevant to the Decision	
Pointers for assessing the indicators for capacity – it is not an exhaustive or exclusive list.	**Comments** *Explain what you have done to assist understanding*
Has information been provided in an appropriate format? E.g. has language been simplified, has it been provided in writing/verbally? Provide it in digestible chunks.	
Use of visual aids- would the use of visual aids help the person to understand? If so, have they been used?	
Use of a 3rd party- is specialist support required to help give the information e.g. translator, sign language etc.	
Environment- is the best environment being used for the patient? E.g. Is it quiet, private, would the person find it easier 1:1 rather than with the MDT?	
Would another person be better placed to provide this information or support the patient through the decision e.g. friends/ relatives/ another staff member	
Timing- choose a time of the day when the person is more alert/ receptive. Revisit giving the information,	
Can the individual understand information about the decision? Summary of assessment	

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Four Seasons HEALTH CARE

Retaining Information Long Enough to Make a Decision	
Pointers for assessing the indicators for capacity – it is not an exhaustive or exclusive list.	**Comments** *(explain what you have done to assist retention of information)*
Has the person been provided with information both verbally, in writing or in any other format that they can refer to e.g. Makaton, drawings, recorded information etc.	
Has information been repeated on numerous occasions?	
Can the individual relay the information back to you?	
Has a third party been engaged to assist e.g. specialist advocate, friend, relative etc.?	
Can the person retain information for long enough to make the decision? *Summary of assessment*	*Note that the individual only need be able to retain information for long enough to make the decision.*

Using or Weighing Information as Part of the Decision Making Process	
Pointers for assessing the indicators for capacity – it is not an exhaustive or exclusive list.	**Comments** *(explain what you have done to assist the person in weighing up information)*
Has the person been told why they need to make this decision?	
Have the 'pros and cons' of this particular treatment been explained?	
Have alternatives been explained?	
Have the likely success and risks/side effects been explained?	
Does the person understand the consequences of refusing the treatment or not making a decision?	
Can the individual use or weigh the information as part of the decision making process? *Summary of assessment*	

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Four Seasons HEALTH CARE

Communicating the Decision	
Pointers for assessing the indicators for capacity – it is not an exhaustive or exclusive list.	**Comments** *(Explain what you have done to assist the person to communicate their decision)*
Is a 3rd party expert necessary e.g. a translator, sign language, speech and language therapist?	
Is appropriate support present to support the patient e.g. advocate, family, friends?	
Has non-verbal communication been considered? e.g. eye blinking, hand squeeze etc.	
Have technical aids to communication been considered e.g. voice board	
Can the person communicate their decision? *Summary of assessment*	

	Details of Person Completing this Form
Name	
Designation	
Signature	
Date	

Names of people involved in this assessment (ensure you include the individual, relatives, friends etc. where involved)	
Name	**Designation**

E.5 Assessment of Best Interests Form

University of Salford MANCHESTER

Four Seasons HEALTH CARE

04 – Determination of Best Interests

Personal Details of Individual for Whom Capacity is Being Assessed	
First Name	
Surname	
Date of Birth	
Gender	
Religion	
Ethnicity	

Confirmation of Capacity Assessment		
Has the Person been assessed as lacking capacity to make this specific decision at this particular time?	Yes	Date of capacity assessment completed on form MCA1: …………………………………………………………………
	No	If the answer to this question is 'no', you must complete a capacity assessment and document it appropriately on Form MCA1

The Decision to be Made

Provide details of the decision that needs to be made

_____________________________ has been selected to participate in a research study that aims to identify key factors relating to their movement that may be able to predict when they are at highest risk of falling. Measures to reduce the risk of falls have been implemented and have included a review of previous falls and any discernible patterns, appropriate environment, appropriate footwear, review of medication, (add any other measures that may have been taken).

____.

____.

____.

Despite these measures, _________________________ continues to experience a high number of falls and therefore it is felt that it may be beneficial for them to participate in this study.

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Test of Capacity		
Does the person have an impairment of, or a disturbance in the functioning of the mind or brain? *Examples may include; conditions associated with some forms of mental illness; long term effects of brain damage; dementia; concussion; symptoms of drug or alcohol abuse*	Yes **Continue rest of assessment**	No **The person does not lack capacity under the MCA**
Does the impairment or disturbance mean that the person is unable to make a specific decision when they need to?	Yes **Evidence details of assessment below**	No **The person does not lack capacity under the MCA**
Does the person have capacity to make this decision at the time it needs to be made?	Yes	No

Evidence for Findings - Understanding Information Relevant to the Decision	
Pointers for assessing the indicators for capacity – it is not an exhaustive or exclusive list.	**Comments** *Explain what you have done to assist understanding*
Has information been provided in an appropriate format? E.g. has language been simplified, has it been provided in writing/verbally? Provide it in digestible chunks.	
Use of visual aids- would the use of visual aids help the person to understand? If so, have they been used?	
Use of a 3rd party- is specialist support required to help give the information e.g. translator, sign language etc.	
Environment- is the best environment being used for the patient? E.g. Is it quiet, private, would the person find it easier 1:1 rather than with the MDT?	
Would another person be better placed to provide this information or support the patient through the decision e.g. friends/ relatives/ another staff member	
Timing- choose a time of the day when the person is more alert/ receptive. Revisit giving the information,	
Can the individual understand information about the decision? Summary of assessment	

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Retaining Information Long Enough to Make a Decision	
Pointers for assessing the indicators for capacity – it is not an exhaustive or exclusive list.	**Comments** *(explain what you have done to assist retention of information)*
Has the person been provided with information both verbally, in writing or in any other format that they can refer to e.g. Makaton, drawings, recorded information etc.	
Has information been repeated on numerous occasions?	
Can the individual relay the information back to you?	
Has a third party been engaged to assist e.g. specialist advocate, friend, relative etc.?	
Can the person retain information for long enough to make the decision? *Summary of assessment*	*Note that the individual only need be able to retain information for long enough to make the decision.*

Using or Weighing Information as Part of the Decision Making Process	
Pointers for assessing the indicators for capacity – it is not an exhaustive or exclusive list.	**Comments** *(explain what you have done to assist the person in weighing up information)*
Has the person been told why they need to make this decision?	
Have the 'pros and cons' of this particular treatment been explained?	
Have alternatives been explained?	
Have the likely success and risks/side effects been explained?	
Does the person understand the consequences of refusing the treatment or not making a decision?	
Can the individual use or weigh the information as part of the decision making process? *Summary of assessment*	

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Communicating the Decision	
Pointers for assessing the indicators for capacity – it is not an exhaustive or exclusive list.	**Comments** *(Explain what you have done to assist the person to communicate their decision)*
Is a 3rd party expert necessary e.g. a translator, sign language, speech and language therapist?	
Is appropriate support present to support the patient e.g. advocate, family, friends?	
Has non-verbal communication been considered? e.g. eye blinking, hand squeeze etc.	
Have technical aids to communication been considered e.g. voice board	
Can the person communicate their decision? *Summary of assessment*	

	Details of Person Completing this Form
Name	
Designation	
Signature	
Date	

Names of people involved in this assessment (ensure you include the individual, relatives, friends etc. where involved)	
Name	**Designation**

E.6 Participant Consent Form

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Four Seasons HEALTH CARE

05a – Consent Form

Peel Trust Falls Project

Project Title:
A novel body-worn falls detection system: development and evaluation in the frail elderly population.

University of Salford Researcher:
Robert Broadley
Four Seasons Health Care representatives:
Roberta Roccella (Head of Quality and Governance)
Dr Haydn Williams (Datix Manager)

	Initial box to confirm
I confirm that I have read and understand the **Participant Information Sheet** (version 2.1) for the above study and have had the opportunity to ask questions.	
I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without my care or legal rights being affected.	
I agree to information relating to any fall that may occur being collected for inclusion in this study.	
I agree that my anonymised data can be kept in the repository within the University of Salford and accessed, with permission, by researchers at the university.	
To participate: • You must NOT have an existing skin condition (such as psoriasis or eczema) that would be affected by the application of a medical grade dressing. • You MUST live in a Four Seasons Care Home. • You must NOT be wheelchair bound at all times. I confirm that I am not in breach of any of the above conditions.	

By signing this consent form I understand that after the study my anonymised data will be safely archived and may be made available to other researchers at the University of Salford data and elsewhere. However, it will not be possible to identify me from this data.

Name of participant: ____________________

Signature: ____________ **Date:** ____________

Name of person taking consent: ____________________

Signature: ____________ **Date:** ____________

05a – Participant Consent Form _ IRAS ID 225139_2017-11-20_v2.0

E.7 Consultee Declaration Form

University of Salford MANCHESTER

Four Seasons HEALTH CARE

05b – CONSULTEE DECLARATION FORM

Title of Project: A novel body-worn falls detection system: development and evaluation in the frail elderly population.

Please initial box

I ________________ have been consulted about ____________________ participation in this research project. I confirm that I have read and understand the information sheet. I have had the opportunity to ask questions about the study and understand what is involved.	☐
In my opinion they would have no objection to taking part in the above study.	☐
I understand that I can request they are withdrawn from the study at any time, without giving any reason and without their care or legal rights being affected.	☐
I understand that relevant sections of their care record and data collected during the Study may be looked at by responsible individuals from Four Seasons Health Care and Salford University or from regulatory authorities, where it is relevant to their taking part in this research.	☐
If your friend or relative regains capacity they will be asked to give their consent to continue with the study.	☐

________________	________________	________________
Name of Consultee	Date	Signature

Relationship to participant:

________________	________________	________________
Person undertaking consultation Name	Date	Signature

________________	________________	________________
Researcher	Signature	Date

When completed: 1 (original) to be kept in care record, 1 for consultee; 1 for researcher site file

05b – consultee_declaration_form-IRASID-225139_2017-11-20_v1.0

E.8 Staff Training on Data Collection Handout

University of Salford MANCHESTER

Four Seasons HEALTH CARE

Peel Trust Falls Project

Information on Data Collection

1. Introduction

Falls are one of the serious and common health related problems amongst the older adult population. Over 40,000 falls have been recorded in the past year in Four Seasons Health Care homes alone. Accurate detection of falls and immediate help would greatly minimise the adversities following a fall. However, current fall detection systems suffer from a high rate of false alarms.

2. Project Aims

Short Term:

- Collect one of the world's largest fall datasets

Medium Term:

- Improve understanding of fall movements
- Develop robust fall detection
  - High sensitivity (detect the vast majority of falls)
  - Low rate of false alarms

Long Term:

- Develop fall prediction technology

3. Benefits of Taking Part

Reports of activity data for each resident can be used to understand daily routines and activity levels. These reports also show night time activity and can be used to determine if the residents get up at night, and if so how frequently.

On completion of data collection, we provide certificates to homes, staff and residents. The certificates can be used to demonstrate to commissioners and regulatory bodies a commitment to research, innovation and quality improvement. Staff can use certificates as evidence for their CPD portfolio.

4. Protocol

- Residents wear a small movement monitor for 6 x 10day periods
- Every 10 days the monitors need to be returned to the university for recharging and reprogramming
- The medical dressing used to secure the monitor should be changed after 5 days
- The monitor should be checked every 2 days to ensure it is still in place and the dressing is not coming loose

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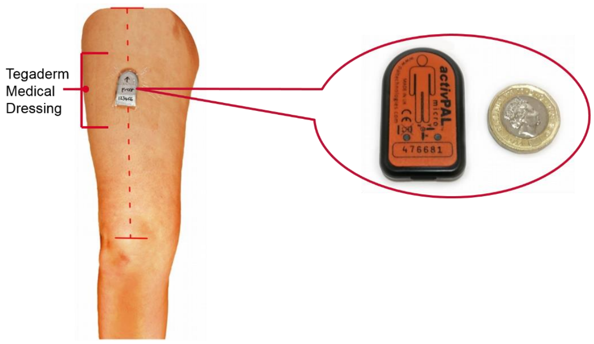
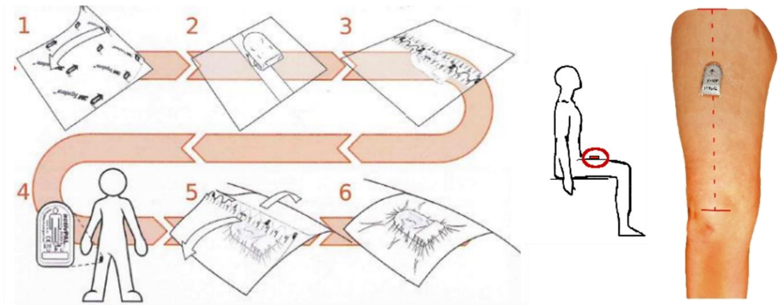
5. The activPAL Monitor



6. Attaching the Monitor



Instructions can be found on the back of the Device Monitoring Sheet

7. When You Should Remove the Monitor

- Bathing (showering is OK, providing Nitrile sleeve is intact)
- Hospital or a medical appointment outside the home
- Changing the dressing
- Returning to the University

8. When You Must Remove the Monitor

- If the resident no longer wants to take part in the study
- If the consultee no longer wants the resident to take part in the study
- If the resident develops a skin breakdown or skin condition such as psoriasis or eczema

9. Withdrawal Procedure

Any resident or consultee who wants to withdraw can do so at any time. They do not need to give a reason. No "approval" is required from the study organisers. If a resident or their consultee wishes to leave the study a note should be made in the care plan, the Home Manager and Salford University should be informed by email or telephone.

10. Device Monitoring Sheet

Every time the monitor is removed (for any reason) this should be recorded on the device monitoring sheet (document 06). It is more important to accurately record attaching or removing than it is to try and keep the device on the leg all the time. Device monitoring sheets should be returned to Salford University with each monitor and a new monitoring sheet will be sent with the replacement monitor.

Peel Trust Falls Project – Device Monitoring Sheet

Home Name: ____________________________ **DATIX Person ID:** _ _ _ _ _ _

Left or Right Thigh? Circle	Date and Time Attached	Date and Time Removed	Reason for removing / Any other comments	Name and Signature of Staff
L R	17/01/2018 15:00	19/01/2018 09:30	Bathing	
L R	19/01/2018 10:00	22/01/2018 09:30	Swap dressing	
L R	22/01/2018 09:30	28/01/2018 11:00	Return to University	
L R				
L R				
L R				
L R				
L R				

Participant name: ____ Remove this section before returning to Salford University

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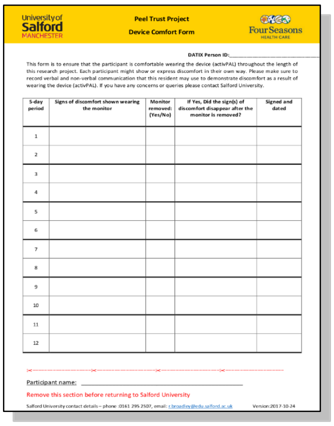
11. Device Comfort Form

For residents who do not have capacity to consent to take part in the study, or who may have difficulty communicating verbally, the device comfort form must be completed at least every 5 days. It is to ensure that taking part in the study is not causing discomfort. It is preferred to complete the device comfort form when the dressing is changed after 5 days and when the monitor is removed to be returned to the university. If the resident shows signs of discomfort due to taking part in the study at any other time this should also be recorded. Any signs of discomfort should be reported to Salford University as soon as possible and if discomfort is serious participation should be temporarily withdrawn, pending advice from the University.


Peel Trust Project

Device Comfort Form

DATIX Person ID:________________

This form is to ensure that the participant is comfortable wearing the device (activPAL) throughout the length of this research project. Each participant might show or express discomfort in their own way. Please make sure to record verbal and non-verbal communication that this resident may use to demonstrate discomfort as a result of wearing the device (activPAL). If you have any concerns or queries please contact Salford University.

5-day period	Signs of discomfort shown wearing the monitor	Monitor removed: (Yes/No)	If Yes, Did the sign(s) of discomfort disappear after the monitor is removed?	Signed and dated
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				

Participant name: ________________

Remove this section before returning to Salford University

Salford University contact details – phone :0161 295 2507, email: r.broadley@edu.salford.ac.uk Version:2017-10-24

12. Recording Falls

Continue to record all fall incidents on DATIX as you are already doing.

Without accurate recording on Datix we can't identify the falls and the data is useless!

Where possible, the direction in which the resident fell (e.g. forwards, backwards, to the side) and the position in which they were found should be recorded on DATIX.

13. Receiving and Returning Monitors

E.9 Wear Time Record

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Peel Trust Falls Project – Device Monitoring Sheet

Home Name: ____________________ **DATIX Person ID:** _ _ _ _ _ _

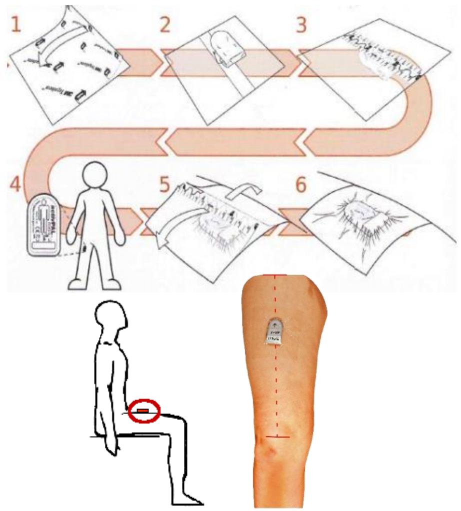
Left or Right Thigh? Circle	Date and Time Attached	Date and Time Removed	Reason for removing / Any other comments	Name and Signature of Staff
L R				
L R				
L R				
L R				
L R				
L R				
L R				
L R				

Participant name: ____________________

Remove this section before returning to Salford University

Attaching the monitor:

The activPAL monitor should be encased in a white nitrile sleeve to provide water resistance. Please check the nitrile sleeve is intact before attaching the monitor, should the sleeve be damaged please return the monitor to Salford University.



1. Remove the backing sheet from the Tegaderm dressing.
   Once separated, you will be left with a clear piece of dressing.
2. Place the activPAL face down in the middle of the sticky side of the Tegaderm dressing. (Face down means that the side labeled front should be facing down on the sticky clear bandage.)
3. Pick up the Monitor and Tegaderm, holding the edges of the Tegaderm dressing.
4. Position the device on the middle of the front of the participant's thigh (halfway between the knee and the hip).
   The curved part of the activPAL should be pointing towards the hip.
5. Press the clear bandage down on the leg firmly, to ensure that it is stuck in place.
6. Peel off the top liner of the Tegaderm, start from the middle and work out towards the edges to smooth out the air bubbles and wrinkles as much as possible.

Don't forget to complete the "Device Monitoring Sheet" each time you attach or remove a monitor.

Other notes:

- Skin irritation due to dressing can occur. If this happens, attach the monitor to the other leg. If the participant continues to experience irritation, then take the monitor off and contact one of the study team (details below).
- In the event of skin irritation, the Home Manager or Deputy Home Manager should also be informed, and a record made on the Falls Project "Device Monitoring Sheet" and in the resident's care plan.
- The monitor is water resistant (if encased in a nitrile sleeve), so participants can wear it whilst showering, but it is not to be worn while bathing. Therefore, make sure to remove the device when bathing and reapply it afterwards.

If you have any problems or questions please contact: Rob Broadley (0161 295 2507) at the University of Salford, or Sharon Clark (07710 064 004), Roberta Roccella (07583 091 698), or Haydn Williams (07733 893 019) at Four Seasons Health Care.

E.10 Device Comfort Form

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Peel Trust Project

Device Comfort Form

Four Seasons HEALTH CARE

DATIX Person ID:______________________________

This form is to ensure that the participant is comfortable wearing the device (activPAL) throughout the length of this research project. Each participant might show or express discomfort in their own way. Please make sure to record verbal and non-verbal communication that this resident may use to demonstrate discomfort as a result of wearing the device (activPAL). If you have any concerns or queries please contact Salford University.

5-day period	Signs of discomfort shown wearing the monitor	Monitor removed: (Yes/No)	If Yes, Did the sign(s) of discomfort disappear after the monitor is removed?	Signed and dated
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				

✂------------------✂------------------✂------------------✂------------------

Participant name: ____

Remove this section before returning to Salford University

Salford University contact details – phone :0161 295 2507, email: r.broadley@edu.salford.ac.uk Version:2017-10-24

F Fall Signal Identification Application

F.1 Application Development

An application was developed to facilitate the verification of the fall times. The process of verification consisted of checking the accelerometer signal around the reported time and the identification of the point which matched the description in the fall report. If no matching signal could be identified then this was recorded with a reason. To increase the reliability of the results, two experts independently analysed the accelerometer signals to identify the falls. Where there was disagreement the experts met for discussion and to agree, if possible, on (1) whether the description from the fall report suggested the incident was a valid fall, (2) whether the fall could be identified and if not why, and (3) which point in the accelerometer signal corresponded to the fall.

To facilitate the process a software application was developed. The application was written using Python3, with SQLAlchemy to interact with the database and PyQt5 for the Graphical User Interface (GUI). To support the main application a series of modules written using Python3 and SQLAlchemy were used to automate data management tasks. The application aimed to aid in the following parts of the process:

- Identification of the reported falls for which data were available
- Identification of falls which the current researcher could work on
- Accessing the information contained in the fall reports
- Deciding if the reported fall was valid based on the description from the fall report
- Analysing the accelerometer signals
- Deciding if the fall could be identified in the accelerometer signal
- Marking the identified point at which the fall occurred
- Recording the confidence in the identified point
- Storage of the results

F.1.1 Records of Fall Signal Identification

To keep all data in a single location the records of fall signal identification were added to the fall record table in the SQLite database which was used to record information during the data collection (Section 6.3.1). The relationship between the fall table and others in the database is shown in Figure F.1. The fall table stored all the information from the fall reports received from the care homes, which included the participant ID (for details see 6.2.3.2) and columns for the results of signal identification (Table F.1). The columns for the study phase, file id and disagreement were all automatically populated based on queries of the database. For the study phase and file id, the queries were run before the verification process began, for the disagreement column the query was run after every captured fall had been analysed by two researchers. The other columns each appeared three times, two for the independent analysis and one for the final decision.

Table F.1: Fall table columns for verification process.

Column	**Description**
Study Phase	The phase of the study, relative to the participant, in which the fall occurred ('pre' for before the first recording was made, 'post' for after the last recording, 'between' for in between recordings or 'captured' if during a recording).
File ID	The SHA1 hash of the accelerometer data file identified as potentially containing the fall. This linked to the file table where further information was stored such as the file path.
ID Code	The ID of the user who analysed the data.
Valid	A Boolean indicating whether the fall was deemed valid.
Verifiable	A Boolean indicating whether the fall could be identified.
Unverifiable Reason	The given reason why the fall could not be identified.
Sample No.	The number of the sample in the accelerometer recording which was marked.
Date & Time	The timestamp of the sample in the accelerometer recording which was marked.
Confidence	The given confidence in the marked point.
Disagreement	A Boolean indicating whether researchers disagreed.

F.1.2 Graphical User Interface

The GUI for the application was designed to be simple and easy to use whilst locking the user into following the predefined process. Through a series of dialog windows, the

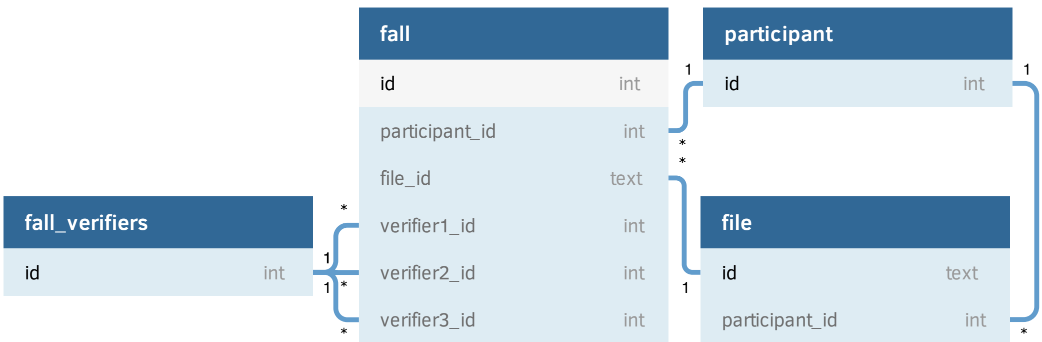

Figure F.1: Relationship between the fall table and others in the database.

user was taken step by step through the fall verification process, with only the necessary information available at each step. To prevent bias the user could only see information about the fall they were currently working on, with no access to their previous work or the work of other users. To remove any potential issues caused by errors in data entry, all interaction with the underlying data was abstracted away, leaving the user free to focus on the analysis. The application handled all interaction with the database, it retrieved data as it was needed and stored the results when the user saved their work. Screenshots of the application's windows and a description of the user interaction can be found in the section which follows (Section F.2).

F.2 The Process of Verifying Falls Using the Application

Upon starting the application, a dialog was presented to the user requesting their user ID (Figure F.2). All work committed to the database was linked to the ID given at the start of the session. Once the user ID was entered, a query was run against the database to find falls which had not yet been rated by two users and which had not been rated by the current user. From the query result, the application selected a fall at random for the user to work on. The random selection was chosen to minimise any effect of learning from previous falls as might happen if all users worked on the falls in the same order.

Information about the chosen fall was queried from the database and presented to the user who then confirmed that the fall was valid (Figure F.3). Falls were not deemed valid if the description indicated that staff had intervened before the faller had come to rest as this would interfere with the faller's motion and there is questionable value in the automatic detection of such an event.

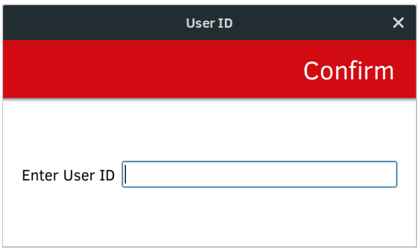

Figure F.2: Fall verification software: user login.

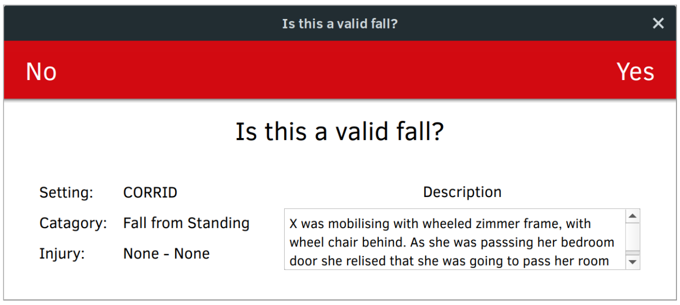

Figure F.3: Fall verification software: dialog to check if a fall was valid based on information from the incident report.

If the user indicated that the fall was valid the accelerometer signal for the fall was loaded and presented to them, along with the description of the fall (Figure F.4 - Image A). The signal was presented on two plots, one showing each of the three axes of the accelerometer and one showing the resultant acceleration. Both plots shared an X-axis of date and time with acceleration in multiples of the acceleration due to earth's gravity (g) on their respective Y-axes. The initial view of the data showed twenty-four hours of data centred around the reported fall time, which was marked by an orange dotted line. However, all data from the complete recording containing the fall was loaded so that the user could scroll through to get an understanding of the faller's daily routines.

The application allowed the user to freely scroll back and forth through the signal and zoom in and out, both in the time dimension only. Following an inspection of the accelerometer signal, the user could either place a marker on the plot where they believed the fall to be or save without placing a marker if no part of the signal matched the described fall. If the user could not identify the fall in the signal, and therefore placed no mark, upon pressing 'Save' a dialog asking why was presented (Figure F.5). The options available were 'non-wear', 'no signal matches description' or 'other'.

A

B

Figure F.4: Fall verification software: main window. A) The main window as it appeared upon loading the data for a fall. B) The main window as it appeared once the user has zoomed in and marked the fall.

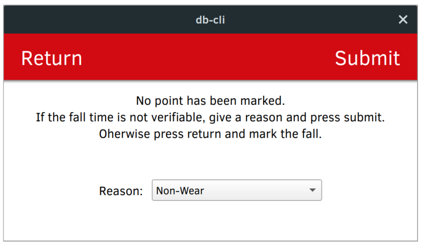

Figure F.5: Fall verification software: not verifiable dialog.

If the user could identify a signal which matched the described fall, they activated the marker by pressing the 'Mark' button and then clicked on the plot to place the mark (Figure F.4 - Image B). To standardise the placement of the marker, it was agreed that all users would mark the point of impact, which presents as a peak in the resultant acceleration signal. To assist the user, the application was programmed to place the mark on the peak in the resultant acceleration nearest to where the user clicked. Following placing a mark on the plot the user pressed save, and the application presented a dialog to request the user's confidence that they had marked the correct point (Figure F.6).

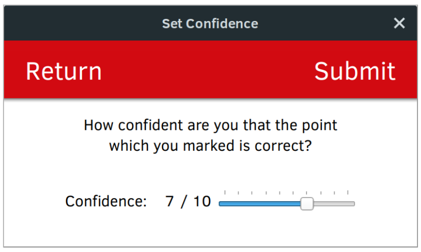

Figure F.6: Fall verification software: confidence dialog.

Upon the user either submitting that the fall could not be verified with a reason why, or the identified point of impact with the confidence in said mark, the application presented a dialog to confirm before committing the results to the database (Figure F.7).

Figure F.7: Fall verification software: commit dialog.

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