Design and Validation of a Fall Event Detection System using Wearable Sensors: A Machine Learning Approach

by

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Ethics Statement

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Abstract

Falls are the number one cause of injury and injury-related deaths in older adults. Nearly one-half of those over age 65 are unable to rise independently after falling, and a significant source of morbidity is the 'long-lie' that often occurs after falling. A wearable sensor system that automatically detects falls can facilitate quicker delivery of care. Such systems can also log information on the nature of the fall to inform prevention efforts. This thesis describes my efforts to develop improved methods for detecting fall-related events in older adults through wearable sensors (i.e. accelerometer and gyroscopes). In particular, I developed and evaluated novel approaches to extend the utility of fall monitoring systems beyond post-impact fall detection, to pre-impact fall detection, near-fall detection and causes of fall detection. In my first study, I conducted laboratory experiments to compare the accuracy of machine learning versus threshold-based approaches for distinguishing falls from daily activities based on wearable sensor data. In my second study, I examined the accuracy of machine learning algorithms in distinguishing falls from real-world fall and non-fall datasets from young and older adults. My third study focused on pre-impact fall detection (detecting falls during the descent phase before impact) which is relevant to the design of active protective gear (e.g., airbags). In particular, I determined how the data window size and lead-time affects classification accuracy based on a single waist sensor. In my fourth study, I developed a near-fall identification algorithm based on machine learning, which could provide biofeedback to the individual of their state of balance. I examined how the number and location of sensors on the body influenced the accuracy of the algorithm in identifying near-fall from activities of daily living. My final study examined the ability of wearable sensors to provide objective evidence on the cause and circumstances of falls, to aid in diagnosing and treating the underlying causes of falls in older adults. My overall efforts advance the potential of wearable sensors (i.e. accelerometers and gyroscopes) for providing objective and clinically relevant information for the prevention and treatment of falls and their related injuries in older adults.

Keywords: older adults; falls; wearable sensors; machine learning; biomechanics; biomedical engineering

Dedication

To my parents.

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List of Acronyms

ADLs	Activities of Daily Living
AP	Anterior/ Posterior
AS	Ascending Stairs
CS	Cross-Step
DS	Descending Stairs
DSL	Descending from Standing to Lying
DSS	Descending from Standing to Sitting
DT	Decision Tree
FN	False Negative
FP	False Positive
HB	Hit and Bump
Inf	Inferior
ISBW	Incorrect Shift of Body Weight
ITDS	Incorrect Transfer while Descending from Standing
ITRS	Incorrect Transfer while Rising from Sitting
KNN	K-Nearest Neighbour
LCC	Loss of Conscious/ Control
LDA	Linear Discriminant Analysis
LFT	Lower Fall Threshold
LR	Logistic Regression
LTC	Long Term Care
ML	Medial/ Lateral
NB	Naïve Bayes
NW	Normal Walking
POG	Picking an Object from the Ground
PSP	progressive supranuclear palsy
RBF	Radial Basis Function
RBK	Robert Bosch Krankenhaus
RSS	Rising from Sitting to Standing
Sens	Sensitivity
Spec	Specificity

SQ	Standing Quietly
STS	Sit-To-Stand
Sup	Superior
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TUG	Timed Up-and-Go

Chapter 1.

Introduction

1.1. Falls in older adults

Falls are a leading cause of unintentional injury hospitalizations and deaths in adults aged 65 and older [1]. Approximately 30% of all older adults, and 50% of older adults residing in long-term-care (LTC) facilities, fall at least once per year [2-4]. Falls also place burden on family members and care providers. Almost half of older adults who fall experience a minor injury, and 5% to 25% sustain a serious injuries such as fractures or traumatic brain injuries [5]. About 62% of injury-related hospitalizations for all older adults are the result of falls, and the direct costs associated with falls among older adults in Canada are estimated to be over $2 billion annually [6]. Of all injuries from falls, hip fractures cause the greatest health problems and the greatest number of deaths. About 27,000 hip fractures occur each year in Canada [7] and more than 90% are due to falls. Relatively rare in young adults, the frequency of hip fracture increases exponentially with age [8], and the average fracture patient in Canada is 82 years old [9]. Over 20% of hip fracture patients die within a year of the event [10-13]. However, even when no injury occurs, falls can cause negative health outcomes, such as fear of falling, loss of autonomy, isolation, confusion, immobilization, depression and, increased risk for future falls [14-16]. Furthermore, without improvements in prevention, fall-related injuries are expected to increase substantially in future years due to demographic shifts towards a more aged population [7, 17, 18].

In Canada, adults over age 65 are the fastest growing segment of the population. According to Statistics Canada, in 2011, an estimated 15% of Canadian population (approx. 5.0 million Canadians) were 65 years of age or older. This represents a 50% increase over the past three decades (since 1981). Furthermore, this number is

expected to double in the next 25 years to 10.4 million by 2036 [19]. With the demographic shift towards an increasingly aged population, there is a clear need for improved strategies to prevent and manage the burden associated with falls and fall-related injuries in seniors. It is estimated that a 20% reduction in falls would translate to 7,500 fewer hospitalizations and 1,800 fewer permanently disabled older adults in Canada, and an overall savings of $138 million annually [20].

1.2. Consequences of falls in older adults

1.2.1. Injuries due to falls

Falls are the cause of 10-15% of all emergency department visits [21] and 50% of injury-related hospitalizations among older adults [22]. Older adults hospitalized for fall-related trauma are discharged to nursing homes more often than those hospitalized for other reasons. The most common reasons for fall-related hospital admission are bone fractures, head injuries, joint strains and sprains, soft tissue injuries, muscle contusions, cuts and abrasions [23, 24].

Of all injuries from falls, hip fractures cause the greatest health problems and the greatest number of deaths. While only 2.9% of all falls result in hip fracture [25], falls are so common that the overall mortality and morbidity rates are substantial [26, 27]. Four percent of hip fracture patients die in the hospital immediately following the injury [28], and 23% are dead within the first year of their injury [29]. Older adults who survive hip fracture experience a substantial decline in mobility, physical activity, and functional independence [30]. Half of all older adults hospitalized for hip fracture cannot return home or live independently after the fracture [31, 32]. While the overall number of hip fractures has continued to increase annually with the aging of the population, in Canada (and several other countries) there has been a plateau in recent years in the age-adjusted rate of hip fractures – perhaps related to nutrition, fall prevention efforts, and osteoporosis medications [33, 34].

Falls are the underlying cause of 60% of head injuries in older adults, the most significant of which is traumatic brain injury (TBI) [35, 36]. The one-year survival rate for

older adults after severe TBI is as low as 20% [37-40]. Furthermore, in contrast to hip fractures, the age-adjusted rate of fall-related TBI in those over age 80 has increased 3-fold over the past 30 years in Finland [41] and has more than doubled over the past decade in Australia [36]. TBI now accounts for 50% of deaths from falls in older adults. The causes for these trends have are poorly understood, and are thought to relate to an increase in the frequency of falls in the frailest seniors [42] and/ or the increased use of anticoagulants, which increase the risk for an intracranial bleed following head impact [36, 43, 44].

Distal forearm fractures most often occur when attempting to arrest the fall with the stretched arm(s). However, after age 70, there is a decrease in the incidence of forearm fractures. At the same time, there is an increase in the frequency of head trauma and hip fractures due to falls. These trends have been attributed to a decline in the frequency and forcefulness of upper limb fall arrest strategies that may protect the hip and head, while increasing the risk for distal radius fracture [1, 45].

1.2.2. Fear of falling

Fear of falling is a common consequence of falls among older people. A survey conducted by Cummings et al. [16] reported that approximately 40-60% of seniors who had fallen expressed fear of falling, and 23-30% who had not fallen expressed fear of falling. Fear of falling is a risk factor for future falls. It decreases quality of life [14-16] and increases the rate of physical decline and ability to independently perform activities of daily living [46, 47]. Fear of falling can also lead to self-imposed isolation and reduce mobility, which in turn further diminishes the quality of life of the older adults, in particular among recurrent fallers and those who have sustained serious injuries [47]. A conservative estimate indicates that up to 50% of people who fall avoid normal daily activities because they fear additional falls and injuries [48]. This may cause many older adults to eventually become chair bound or bedridden, reluctant to attempt independent activities and socially isolated, thus, increasing complications which are associated with immobility.

1.2.3. Long-lie after falling

Another serious consequence of falling is the “long-lie” condition, where a faller is unable to get up and remains on the ground for more than an hour after a fall. Up to 47% of non-injured fallers are unable to rise from the floor without assistance [49, 50]. Long-lies can result in substantial damage to the individual’s body and morale. Lying on the floor for an extended period of time often results in several medical complications such as muscle damage, pneumonia, pressure sores, dehydration and hypothermia [51-54]. Long-lies are also associated with high mortality rates among older adults [52]. It is estimated that half of the older adults who experience a long-lie die within 6 months [55], even if no direct injury from the fall has occurred. Long-lies occurred in more than 20% of elderly people admitted to hospital as a result of a fall [56]. Hence, detection of a fall, either through automatic fall detection or through a personal emergency response system, should reduce the frequency and consequences of long-lies by reducing the time between the fall and the arrival of medical attention [50].

1.3. Near-fall events in older adults

An individual’s risk for falls depends on how often they experience imbalance episodes, and their ability to quickly recover balance after these events. “Near-falls” can be defined as loss of balance followed by successful balance recovery (by stepping, grasping, or feet-in-place responses). The cause of imbalance is often due to complex interactions between multiple risk factors (intrinsic and extrinsic risk factors), leading to a slip, trip, or incorrect shift of bodyweight. Episodes of near-falls are common among older adults [57-59]. Near-falls are clinically relevant markers of fall risk and an improved understanding of their prevalence and nature should provide a more robust estimate of fall risk and customized approaches to reducing falls.

1.4. Cause and circumstances of falls

Falls have been defined as sudden changes in postural stability causing an individual to unintentionally land at a lower level [60]. In biomechanical terms, most falls

can be defined as loss of stable upright posture due to body movements (and lack of appropriate corrective actions), which displace the body's center of gravity beyond its base of support. Researchers have examined a variety of strategies to prevent falls in older adults, including exercise-based strength and balance conditioning [61, 62], elimination of environmental hazards, optimization of medications, and Vitamin D supplements [63-65]. Most of these strategies have shown moderate success in community-dwelling older adults, but have been less effective in reducing falls in frailer older adults in the long-term care setting [66-68].

The development of improved approaches to preventing falls in older adults requires a better understanding of the mechanisms that cause these events. Most experts agree that falls in older adults often occur from interactions between environmental hazards (e.g., obstacles in a path of travel, poor lighting, slippery floors, uneven surface, footwear, clothing, inappropriate walking aids or assistive devices [69-75]) and increased susceptibility to hazards from the accumulated effects of age and disease (e.g., chronic diseases, muscle weakness, gait and balance impairment, medication use, vision impairment, and cognitive impairment [72, 76, 77]). Accordingly, while most falls in young and middle-aged adults occur during sports or vigorous activities, falls in older adults often occur while performing routine daily activities such as walking, turning, reaching and transferring [78]. The most common self-reported causes of falls in older adults are slips and trips, along with "loss-of-balance", "leg gave away" or "don't know" [79, 80].

Only recently has more detailed evidence emerged of the circumstances of falls in older adults, to guide fall prevention and management. In particular, recent findings from our laboratory [81], based on the analysis of video footage of 227 falls experienced by 130 older residents of long-term care, indicate that 48% of falls occur while walking, and 86% are collectively due to incorrect shift of bodyweight (41%), tripping (21%), hit/ bump (11%), collapse/ loss of conscious (10%) and slipping (3%).

1.4.1. Inaccuracies in self-reported falls

Most clinical research on falls, and tracking of falls in care settings, is based on fall incident reports. However, most falls among older adults go un-witnessed [82-85], and incident reports therefore rely on the ability of the individual to accurately recall and describe the event. Individuals are likely to misreport fall events due to forgetting or denying falls, especially those not resulting in injury [86, 87]. Improved techniques are required to detect and characterize falls in order to guide prevention and treatment strategies.

1.5. Technology for fall detection

Fall-detection technologies are designed to enable rapid detection and delivery of clinical care to older adults who have experienced a fall. In the future, fall monitors should be able to help care providers by gathering information on the circumstances of the fall, allowing for improved prevention strategies. The existing fall detection systems can be divided into two categories: (i) ambient systems and (ii) wearable systems.

1.5.1. Ambient sensors

Ambient fall detection systems are considered to be “passive” systems since, once installed, they do not rely on daily decisions by the user to utilize the device. Such systems include video cameras, infrared cameras, or acoustic sensors mounted on the wall or ceiling, pressure sensors or vibration sensors embedded in the floor, and pressure sensors embedded in furniture (Table 1.1). While privacy concerns may limit user acceptance and adherence with camera-based systems, several groups have examined the ability of camera-based fall detection systems to automatically detect falls [88-95]. For example, Yu et al. [94] proposed a video-based system which identified falls by analyzing the amplitude of shape changes and calculating the duration of ‘abnormal’ postures. Background subtraction was applied to distinguish moving objects, and body silhouettes were used to improve resident privacy. The proposed system exhibited 100% sensitivity and 97% specificity in detecting simulated falls in the laboratory, although occlusions and multiple moving objects reduced the accuracy. Similarly, Belshaw et al.

[95] used a single camera to classify fall and non-fall activities, based on extraction of silhouette features, lighting features, and multiple moving objects. A wide-angle lens was used to capture maximum volume. The accuracy in detecting falls of three pattern recognition methods (logistic regression, neural network, and support vector machine) was compared. Out of the three methods, the neural network achieved the best performance with a fall detection rate of 92% and a false detection rate of 5%. Finally, Stone et al. [96] presented a two-state fall detection technique based on 3D video data collected by Miscrosoft Kinect cameras, that was tested with 3339 days of continuous data, including 454 falls (445 performed by stunt actors and 9 occurring naturally in older adults). The proposed system used a machine learning based ensemble of decision tree algorithms, which provided 95% sensitivity in distinguishing falls from non-fall activities. Furthermore, when compared to standard video cameras, the Kinect is less affected by ambient lighting, since it projects infrared dot patterns, which are then reflected back and received by the CMOS camera to compute the depth of the scene.

Alwan et al. [97] examined the ability of vibration sensors embedded in the floor to detect falls. Data were obtained by dropping an anthropometric dummy and various objects on the floor. The floor vibration system provided 100% sensitivity and specificity in distinguishing falls from the dummy from different dropped objects. Zhang et al. [98] proposed a fall detection system consisting of 3 infrared camera and 2 pressure mats. The system provided 100% specificity and 59% to 100% sensitivity in detecting falls, depending on the fall scenarios used in the evaluation.

Acoustic sensors have been also used for detecting posture and falls [99-101]. Li et al. [99] developed an acoustic fall detection system (acoustic-FADE) that automatically detected a fall. The fall detection system consisted of a circular microphone array that captured the sounds in a room, located the source, and classified it as fall or non-fall. Based on the analysis of simulated falls and non-falls, performed by 3 stunt actors, the system was able to distinguish falls from non-falls with 100% sensitivity and 97% specificity.

1.5.2. Wearable sensors

Over the past decade, there has been a great deal of research on the development of methods to automatically detect falls based on wearable inertial sensors (Table 1.2). Such systems include accelerometers, gyros, magnetometers, tilt sensors and/ or barometric pressure sensors [102-123]. A traditional barrier to the adoption of wearable sensor technology has been the size and weight of the sensors, which has limited their suitability for long-term monitoring. However, recent advances in the miniaturization of sensor hardware has enhanced the feasibility of theses systems. Wearable sensors have advantages over ambient sensors in terms of ease of installation, coverage area, and privacy.

The accuracy of various systems has been measured in laboratory experiments, involving young adults falling onto gymnasium mats, and undertaking various activities of daily living (ADLs). The most common anatomical site for mounting inertial sensors is the pelvis [106, 114, 124, 125], although researchers have shown similar accuracy for sensors mounted at the head, sternum, thigh and wrist [102, 103, 105, 112, 113, 125, 126]. Interestingly, there are no data on the accuracy of the only wearable fall sensor that is currently sold - the Philips Lifeline pendant-based sensor [127]. Most fall detection algorithms are threshold-based (relying on the uniquely large acceleration occurring at the instant of impact from the fall), although many also incorporate information on posture (indicative of the individual lying on the floor after the fall). For example, Bourke et al. [106] recorded signals from a tri-axial accelerometer at the waist during a series of fall and non-fall trials with young adults in the laboratory. The fall detection algorithm analyzed the pre-phase, impact-phase, and recovery-phase of the fall, and showed 100% sensitivity and 100% specificity. Kangas et al. [112] used three tri-axial accelerometers (placed at the head, waist and wrist) and recorded falls and ADLs from three healthy middle-aged volunteers. Fall detection using the waist or head accelerometer showed 97% sensitivity and 100% specificity. Researchers at Centre Suisse d'Electronique et Microtechnique (CSEM), Switzerland [126] developed an automatic fall detection system worn at the wrist. Along with automatic fall detection, the device implemented functionalities such as wireless communication, manual alarm

triggering, data storage and a simple user interface, and achieved 90% sensitivity and 97% specificity in the detection of simulated falls.

Bianchi et al. [128] showed that adding a barometric pressure sensor (to measure altitude) to a waist-mounted accelerometer improved the accuracy of a heuristically-trained decision tree classifier in distinguishing falls from ADLs. When tested in a cohort of 20 young healthy volunteers, the system provided 97.5% sensitivity and 96.5% specificity.

Widespread adoption and recent advances in smartphone technology have led investigators to develop and evaluate fall detection applications that utilize data from the array of embedded smartphone sensors (e.g., triaxial accelerometer, gyros, digital compass, GPS, microphone, and camera). Upon detecting a fall and identifying the location of a faller, the smartphone application sends an instant message to a caregiver or family member via SMS, email and/ or Twitter. One of the first smartphone-based fall detection systems was developed by Dai et al. [129], who designed a threshold-based algorithm based on accelerometer and gyro signals, and tested it in laboratory measures with 15 participants involving falls and ADLs. The system was found to have the best performance when mounted at the waist (as opposed to the sternum or thigh), providing 97% sensitivity 91% specificity. Yavuz et al [130] developed a fall detection system that relied only on the smartphone accelerometer, and found that an algorithm based on wavelet transformation was superior (providing a sensitivity of 85%) to a threshold-based approach in distinguishing simulated falls from ADLs collected from five participants. Similarly, Albert et al. [131] attached a smartphone at the posterior aspect of the pelvis and recorded acceleration data from 15 participants who performed falls. 9 participants kept the smartphone for a week and unscripted ADL data were recorded during that time. Five machine learning fall detection algorithms were evaluated in this study. Support Vector Machines and Logistic Regression classifiers were found to be the most accurate, and provided 98% 10-fold cross validation accuracy in distinguishing falls from ADLs.

The high market penetration of smartphones, even among older adults [132], offers a clear advantage in usability over stand-alone wearable sensor systems.

However, there are several challenges to overcome with these systems. A continuously monitoring fall detection algorithm places high demands on smartphone battery life. Furthermore, most current smartphones incorporate accelerometers that have a limited measurement range (e.g,. +/-2 g) that may too small for accurately separating falls from activities such as sitting down or bumping against an object. Finally, most smartphone-based fall detection algorithms were developed from data acquired with the smartphone placed at the waist and/ or sternum, and not the more common real-life situations of the smartphone carried in a pants pocket or handbag.

Despite exhibiting high classification accuracy in laboratory experiments, inertial sensor based fall detection systems have yet to achieve high market penetration. One barrier to the acceptance is the lack of evidence of their effectiveness in real-world falling scenarios in older adults. The only study we are aware of examining real-world accuracy was conducted recently by Bagala et al. [133], who evaluated 13 fall detection methods (including the Bourke and Kangas algorithms described above) using data from 29 real-world falls experienced by older adults that were recorded with wearable accelerometers. They found that the specificity of the thirteen algorithms averaged 83.0% (SD = 30.3%; maximum value = 98%), and the sensitivity averaged 57.0% (SD = 27.3%; maximum value = 82.8%), considerably lower than the values obtained with simulated falls. Furthermore, the number of false alarms generated during a single day of monitoring ranged from 3 to 85. Clearly, additional field studies of this type, incorporating longer durations and larger number of falls, are required to measure and refine the real-life performance of fall detection algorithms based on wearable sensors.

1.6. Experiment protocol for realistic fall simulations

As described in Section 1.5.2 and Table 1.2, the development and testing of wearable fall detection systems has relied on data from laboratory experiments where young adults wear the sensor system while performing simulated falls and ADLs. There are important limitations to these experiments. Ethical constraints have generally required that participants falls onto a padded mattress to avoid injury. Participants are often instructed to self-initiate their fall from standing, directing their fall in the forward, backward or sideways direction, without attempting to recover balance (e.g., by

stepping) or arresting the fall with the upper limbs. The movement patterns of the fall may bear little resemblance to real-life falls in older adults, and this limits the external validity of the test data, and accuracy of the system in real-life [133].

As described in Section 1-4, recent findings from our laboratory [81] provide insight on the most common causes of imbalance and activities associated with falls in older adults in long-term care, to inform the design of more realistic fall simulations. Based on the analysis of video footage of 227 falls in 130 residents (or mean age 78 yrs (SD = 10)), we found that approximately 48% of falls occurred while walking, and 86% of the falls were collectively due to incorrect shift of bodyweight (41%), trip (21%), hit/ bump (11%), collapse/ loss of conscious (10%) and slip (3%). These falling scenarios are substantially different from the ones employed in the past for simulating falls in the laboratory environment.

1.7. Fall detection methods

Methods for fall detection based on wearable sensors can be broadly categorized into threshold-based algorithms (by far the most common approach) and machine learning-based algorithms. A robust fall detection method should exhibit both high sensitivity (ability to detect falls when they occur) and high specificity (low rate of false-positives).

Threshold-based algorithms detect falls by monitoring whether one or more parameter values exceed a threshold value. When compared to machine learning-based approaches, threshold-based techniques are simpler to implement and computationally less demanding. While system sensitivity and specificity has been reported to be high in laboratory experiments, accuracy appears to be substantially lower in distinguishing real-life falls from ADLs [133].

Over the past decade, there has been rapid emergence of machine learning-based data classification techniques as an alternative to traditional threshold-based methods [93, 131, 134]. Machine learning algorithms can be defined as computational adaptive algorithms that can improve performance when provided with examples

(training data). They are particularly suitable for classification problems when the dataset demonstrates complex patterns [135]. These algorithms can be developed and trained using different types of learning concepts, but the two most common are supervised learning and unsupervised learning. In supervised learning, algorithms are trained with data that has examples of input vectors with their corresponding output vectors, or in other words, the data set is labeled. In unsupervised learning, the training data is comprised of input vectors with no labeled outputs. Algorithms developed via unsupervised learning have the goal of discovering groups of similar examples, usually clustering them according to their proximity in the input space. For human activity and fall classification, it is more common to use supervised learning versus unsupervised learning algorithms [135]. Therefore, this thesis will only describe the use of the former in classifying falls and fall related events using body worn sensor signals. Similar to other supervised machine learning applications, fall classification requires two stages, i.e., training and testing. The training stage initially requires a dataset of measured attributes from individuals performing each fall and daily activity. The data are then divided into time windows to apply feature extraction in order to filter relevant information in the raw signals. Later, learning methods are used to generate a fall detection model from the dataset of extracted features. Likewise, for testing, data are collected during a time window and a feature set is calculated. Such a feature set is evaluated in the a priori trained learning model, generating a predicted label.

The results achieved by the recent studies [93, 131, 134] indicate that machine learning methods can be used to improve the accuracy of automatic fall detection in older adults. However, improved understanding is required of the benefits of this approach over threshold-based techniques in accurately detecting falls with wearable sensors. The six machine learning algorithms used for event classification in this thesis are described in Table 1.3.

1.8. Thesis objectives and summary of studies

The overall goal of my thesis research was to develop improved methods for detecting fall-related events in older adults through wearable sensors (i.e. accelerometer and gyroscopes), and thereby advance the potential of wearable sensors for providing

objective and clinically relevant information for the prevention and treatment of falls and their related injuries in older adults. In particular, my objectives were to develop and evaluate the ability of novel (machine learning-based) approaches to extend the utility of fall monitoring systems in three new areas: pre-impact fall detection, near-fall detection and causes of fall detection. To achieve these objectives, I designed and conducted five studies:

Study 1 (Chapter 2): I conducted laboratory experiments to compare the accuracy of machine learning versus threshold-based approaches for distinguishing falls from daily activities based on wearable sensor data. To enhance the external validity of my laboratory experiment, I examined a library of video sequences of 227 real-life falls in older adults residing in long-term-care facilities [81], and selected seven of the most common falling scenarios (causes of imbalance and activity at the time of falling). I then conducted training session with my young participants, who were trained to mimic (for each fall scenario) the movement patterns in video examples of real-life falls in older adults. In addition, participants simulated a variety of ADLs and near-falls.

Study 2 (Chapter 3): I examined the accuracy of machine learning algorithms in distinguishing falls from ADLs using real-world fall and non-fall datasets from young adults, and older adults recruited from the long-term care or acute care setting.

Study 3 (Chapter 4): My third study focused on pre-impact fall detection (detecting falls during the descent phase before impact) which is relevant to the design of active protective gear (e.g., airbags). In particular, I determined how the data window size and lead-time affects classification accuracy based on a single waist sensor.

Study 4 (Chapter 5): In my fourth study, I developed a near-fall identification algorithm based on machine learning, which could provide biofeedback to the individual of their state of balance. I examined how the number and location of sensors on the body influenced the accuracy of the algorithm in identifying near-fall from activities of daily living.

Study 5 (Chapter 6): My final study examined the ability of wearable sensors to provide objective evidence on the cause and circumstances of falls, to aid in diagnosing and treating the underlying causes of falls in older adults.

Table 1.1. Ambient sensor based fall detection systems

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Redmond et al. (2014) [136]	Passive infrared motion s[92-94]ensors + Pressure mats.	Infrared camera was placed at participant's vicinity. Pressure mats were placed under chair legs, sofa and bed legs.	3 participants (Age: 82-84 years)	176 days were monitored at the retirement village. No fall occurred during that time.	Threshold-based	False positive rate: 0.5 per day
Ma et al. (2014) [137]	Kinect depth camera.	Participant's vicinity.	15 young participants.	Fall trials: (i) backward, (ii) forward, (iii) lateral left and (iv) lateral right. ADL trials: (i) walking, (ii) sitting, (iii) squatting, (iv) bending and, (v) lying.	Extreme learning: Support Vector Machine	Sensitivity: 94%. Specificity: 90%. Accuracy: 92%
Stone et al. (2014) [96]	Kinect depth camera.	Participant's vicinity.	16 elderly participants (Age: 67 - 97 years.)	Approx. 3,339 days of continuous data were recorded, which included 445, falls performed by stunt actors and 9 naturally occurring resident falls.	2-stage algorithm. First, characterizes the vertical state of a person. Second, using machine learning ensemble of decision trees to confirm a fall by using on-ground event features.	Sensitivity 95%.
Mastorakis et al. (2014) [138]	Kinect depth camera.	Mounted on a 204 cm high tripod at less than 7 m from Participants.	8 participants.	Fall trails (n=48). ADL trials (n=112).	Machine learning: Decision tree.	Sensitivity: 100%

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Lee and Chung (2012) [139]	Kinect depth camera.	Participant's vicinity.	Not specified.	Fall trials (n=53): (i) backward, (ii) forward, (iii) lateral left and (iv) lateral right. ADL trials (n=122): (i) walking, (ii) standing, (iii) crouching down, (iv) standing up.	Threshold-based.	Sensitivity: 94%. Specificity: 98%. False positive rate: 2%. Accuracy 97%.
Yu et al. (2013) [94]	Video camera.	Participant's vicinity.	12 participants	Fall trials: not specified. ADL trials: (i) walking, (ii) standing, (iii) sitting and (iv) lying.	Machine learning: Support Vector Machine.	True positive rate: 97%. False negative rate: 0.8%
Li et al (2012) [99]	Acoustic sensor (a circular microphone).	Mounted at the wall approx. 4 m from the participants.	3 participants/ stunt actors.	Falls trials (n=120). ADL trials (n=120).	Machine learning: K-nearest neighbour.	Sensitivity: 100%. Specificity 97%.
Humenberger et al. (2012) [92]	Video camera.	Participant's vicinity.	A professional stunt man was hired for simulating falls.	Fall trials: from (i) standing, (ii) sitting, (ii) lying and (iv) walking. ADL trials: not specified.	Neural Networks.	Accuracy: 90% - 99%

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Zhang et al. (2011) [98]	3 Passive infrared motion sensors. + 2 Pressure mats.	Each infrared sensor was placed in the bedroom, corridor and bathroom of an apartment. Pressure sensors were placed under the mattress in bedroom and in front of the toilet seat.	1 participant	Fall trials: (i) fall with unconsciousness, (ii) fall with failure to recover and (iii) fall with unsuccessful recovery. ADL trials: (i) enter and leave room, (ii) out of bed and dresses to leave room, (iii) in bed, wake up and have a drink and back to sleep, (iv) sit on toilet, and then leave bathroom, (v) bedroom to bathroom, and back to bed, (vi) bedroom to bathroom, back to bedroom.	Threshold-based.	Sensitivity: 59% - 100%. Specificity: 100%
Huan-Wen et al. (2010) [140]	Infrared camera + Pressure sensor.	Infrared camera was placed at participant's vicinity. Pressure sensors were installed in the floor.	Not specified.	Fall trials (n=90). ADL trials (n=90).	Threshold-based.	Sensitivity: 93%. Specificity: 89%. Accuracy: 91%
Liu et al. (2010) [93]	Video camera.	Participant's vicinity.	15 participants (24 - 60 years).	Fall trials: not specified. ADL trials: (i) walking, (ii) standing and (iii) lying down.	Machine learning: K-nearest neighbour.	Accuracy: 82%
Rimminen et al. (2010) [141]	Near-field image sensor.	In the floor.	10 participants.	Fall trials (n=300). ADL trials (n=350).	Markov chain.	Sensitivity: 91%. Specificity: 91%.
Alwan et al. (2006) [97]	Piezoelectric floor vibration sensor.	In the floor.	Anthropometric dummy was used to simulate falls	70 falls using a dummy and 53 object drops were performed.	Threshold-based.	Sensitivity: 100%. Specificity: 100%

Table 1.2. Wearable sensor based fall detection systems

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Kau and Chen (2015) [134]	Smartphone (3D Acc. + e-compass)	Thigh.	Not specified.	Fall trials: 1 type of fall simulated. ADL trials: (i) walking, (ii) running, (iii) sitting down, (iv) going upstairs, (v) going downstairs, (vi) jumping, (vii) treading and (viii) wavering the smartphone up and down.	Machine learning: Support Vector Machine.	Sensitivity: 92%. Specificity: 99%
Liu et al. (2014) [142]	3D Acc. + 3D Gyro.	Sternum.	10 participants (Age: 75±6 years).	Fall trials (n=53): backward falls. ADL trials (n=179).	Threshold-based	Sensitivity: 100%. Specificity: 96%
Woon-Sung et al. (2013) [143]	3D Acc. + 3D Gyro.	Neck (necklace style).	5 participants.	Fall trials: (i) forward, (ii) backward, (iii) lateral left, (iv) lateral right and, (v) falling on the stairs. ADL trials: (i) standing, (ii) sitting in a chair, (iv) sitting on the floor, (v) lying, (vi) walking, (vii) running, (viii) going upstairs, (ix) going downstairs, and (x) bending.	Threshold-based	Sensitivity: 82%. Specificity: 100%
Koshmak et al. (2013) [144]	Smartphone (3D Acc.)	Waist.	7 young participants.	Fall trials: during ice-skating with minor ice-skating skilled people.	Threshold-based	Sensitivity: 100%. Specificity: 90%. Accuracy: 94%
Shih-Hau et al. (2012) [145]	Smartphone (3D Acc. + 3D Orientation sensor)	Sternum + Waist + Thigh.	4 Participants.	Fall trials: not specified. ADL trials: (i) walking, (ii) sitting, (iii) standing up.	Threshold-based	Sensitivity: 77%. Specificity: 74%

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Albert et al. (2012) [131]	Smartphone (3D Acc.)	Posterior aspect of the Waist.	15 Participants performed falls. 9 Participants carried out ADLs (Age: 22-50 years).	Fall trials: (i) forward due to a trip, (ii) backward due to a slip, (iii) left lateral and (iv) right lateral. ADL trials: 9 participants kept the smartphone for a week to record everyday behavior.	Five machine learning algorithms: (i) Support Vector Machines, (ii) Sparse multinomial logistic regression, (iii) Naïve Bayes, (iv) K-nearest neighbour, and (v) Decision trees.	Support Vector Machine and Logistic Regression classifiers are most accurate provided 98% accuracy over 10-fold cross validation.
Yuwono et al. (2012) [124]	3D Acc.	Waist.	8 participants performed fall. 5 participants carried out ADLs (Age: 19 - 28 years).	Fall trial (n=378 fall signals). ADL trials (n=1831 ADL signals): 8 hours of ADL data in a home environment by 3 participants, and 1 additional hour of data from 2 participants while they were exercising.	Machine learning, neural network and multilayer perceptron.	Sensitivity: 98%. Specificity 99% for ADL data and, 96% for exercise data.
Jacob et al. (2011) [146]	3D Acc. + 3D Gyro.	Thoracic vertebrae (T4 + T7 + T10).	3 participants (Age: 22 - 28 years).	Fall trials: (i) forward, (ii) lateral left and (iii) lateral right. ADL trails: (i) sitting down in a chair, (ii) standing up and (iii) walking normal pace.	Threshold-based	Sensors placed at T4 provided the best results. Sensitivity: 100%. Specificity: 100%.
Lee and Carlisle (2011) [116]	Smartphone (3D Acc.)	Waist	18 participants (Age: 29±8.7 years).	Fall trials: (i) forward, (ii) backward, (iii) lateral left and (iv) lateral right. ADL trials: (i) sit-to-stand, (ii) stand-to-sit, (iii) level walking, (iv) walking up and (v) downstairs, (vi) answering the phone, (vii) picking up an object and (viii) getting up from supine.	Threshold-based	Sensitivity: 77%. Specificity: 81%.

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Abbate et al. (2011) [125]	3D Acc.	Waist + Sternum + Head.	4 Participants (Age: 24 - 64 years).	Fall trials: (i) from bed, (ii) almost vertical down from standing (fainting), (iii) after parkinsonian gait, (iv) forward landing on hands first, (v) after a small jump, (vi) forward landing on knees first, (vii) while running, and (viii) from sitting. ADL trial: (i) jumping, (ii) lying quickly on bed, (iii) lying quickly on a mat, (iv) lying quickly on sofa, (iv) parkinsonian gait, (v) running, (vi) sitting quickly in an armchair, (vii) sitting quickly on a chair, and (viii) sitting quickly on a sofa.	Threshold-based	Sensitivity: 100%. Specificity: 100%.
Bourke at al. (2011) [105]	3D Acc.	Sternum.	10 participants (Age: 24.3±3.16 years).	Fall trails (n=420) (detail of the type of falls is in the paper). ADL trials: n/a	Threshold-based	The study provided several pre-impact, impact and post impact parameter thresholds for future fall detection algorithm.
Sim et al. (2011) [123]	Two 3D Acc.	Both shoes.	3 participants (Age: 26±2 years).	Fall trials: (i) forward, (ii) backward, (iii) lateral left and (iv) lateral right. ADL trails: (i) sitting in a chair, (ii) driving for 5 minutes, (iii) picking an object from the ground, (iv) jogging for 5 minutes, (v) putting on/ off the shoes, (vi) ascending and (vii) descending stairs, and (viii) walking for 5 minutes.	Threshold-based	Sensitivity: 81%. Specificity: not specified.

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Chen et al. (2010) [109]	3D Acc.	Waist.	3 participant (Age: 24 years)	Fall trails: not specified. ADL trails: (i) standing, (ii) sitting down, (iii) lying down, (iv) walking, (v) jumping, (vi) going up and (vii) down stairs, and (viii) jogging.	Threshold-based	Not specified.
Dai et al (2010) [129]	Smartphone (3D Acc.)	Waist + Sternum + Thigh.	15 participants (Age: 20 -30 years).	Fall trials: (i) forward, (ii) backward, (iii) lateral left and (iv) lateral right. ADL trails: (i) sitting, (ii) standing, (iii) jogging and (iv) walking.	Threshold-based	Waist was found to be the best position to attach the phone. This location provided, Sensitivity: 97%. Specificity: 91%.
Bourke at al. (2010) [106]	3D Acc.	Waist.	10 young participants (Age: 27.2±3.6 years). 10 older participants (Age: 78.8±5.1 years).	Fall trial (n=240) and ADL trails (n=120) performed by young participants. ADL trails (n=240) and 52.4 hours of unscripted walking trials were carried out for older participants.	Threshold-based	Sensitivity: 100%. Specificity 100%
Kangas et al. (2009) [114]	3D Acc.	Waist.	20 mid-age participants (Age: 40-65 years) performed falls and ADLs. Additional ADLs were recorded from 21 older adults (Age: 58-98 years).	Fall trials: (i) syncope, (ii) tripping, (iii) sitting on empty air, (iv) slipping, (v) lateral fall, (vi) rolling out of bed. ADL trials: (i) sitting down on a chair and getting up; (ii) picking up an object from the floor; (iii) lying down on a bed and getting up; and (vi) walking, including both level walking and walking up and down the stairs.	Threshold-based	Sensitivity: 97%, Specificity: 100%.

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Kangas et al. (2008) [112]	3D Acc.	Waist + Wrist + Head.	3 participants (Age: 38 - 48 years).	Fall trials: (i) forward, (ii) backward, (iii) lateral left and (iv) lateral right. ADL trials: (i) walking, (ii) ascending and (iii) descending stairs, (iv) picking n object from the ground, and posture transitions.	Threshold-based	Head and waist worn sensors provided 100% specificity and 97% sensitivity.
Bourke at al. (2008) [103]	3D Acc. + 3D Gyro.	Sternum.	5 participants (Age: 25.6±1.9 years).	Fall trials: (i) forward falls with legs straight, (ii) forward and (iii) backward falls with knee flexion and (iv) side-falls right with knee-flexion. ADL trails: (i) sitting on a chair, (ii) kneeling on the ground, (iii) bending to pick an object from the ground, (iv) lying on a mat, (v) walking 5 m and (vi) practiced coughing.	Threshold-based	Sensitivity: 100%. Specificity 100%
Bourke at al. (2007) [102]	3D Acc.	Sternum + Thigh.	10 young participants (Age: 23.7±2.2 years) performed falls. 10 older participants (Age: 77±4.3 years) carried out ADLs.	Fall trials: (i) forward falls, (ii) backward falls, (iii) lateral falls left and (iv) lateral fall right all performed with both legs straight and with knee flexion. ADL trials: (i) sitting down and standing up from an armchair, (ii) a kitchen chair, (iii) a toilet seat, (iv) a low stool; (v) getting in and out of a car seat; (vi) lying down and (vii) standing up from a bed and (viii) walking 10 m.	Threshold-based	Sternum sensor position was found to be better and provided 100% Specificity. Sensitivity was not applicable.

Author	Sensor(s) type	Sensor(s) placement	Participants	Falls and ADLs description	Algorithm	Results
Kangas et al. (2007) [113]	3D Acc.	Waist + Wrist + Head.	2 participants (Age: 22- 38 years)	Fall trials: (i) forward, (ii) backward, (iii) lateral left and (iv) lateral right. ADL trials: (i) walking, (ii) ascending and (iii) descending stairs, (iv) picking an object from the ground, and posture transitions.	Threshold-based	Sensitivity: 100%. Specificity: 100%.

Table 1.3. Six machine learning algorithms employed for fall and fall related event classification in this thesis

Machine learning algorithms	Description
Linear Discriminant Analysis (LDA)	LDA finds a linear combination of features that characterizes or separates two or more classes of objects or events. This method transforms a classification problem from high dimensional pattern space to lower dimensional feature space via a group of projection operations, and the projection result has the optimal separability.
Logistic Regression (LR)	LR predicts the probability of occurrence of an event by fitting data to a logit function (logistic function). It is an approach to learning functions of the form $f: X \rightarrow Y$, or $P(Y \mid X)$ where Y is discrete value, and X is predictor vector that may contain either discrete or continuous variables. The best logistic regression parameters for event classification are estimated using training dataset by minimizing the cost function.
Decision Trees (DT)	The DT uses hierarchical classification approach. However, rather than the decision structure being constructed manually by the user, rigorous algorithms exist to automate the process and create a compact set of rules. These algorithms work by examining the discriminatory ability of the features one at a time to create a set of rules, which ultimately leads to a complete classification system.
K-Nearest Neighbour (KNN)	KNN is one of the most fundamental and simplest classification techniques. In KNN, a multi-dimensional feature space is constructed, in which each dimension corresponds to a different feature. The feature space is first populated with all training data points, each of which corresponds to a particular event, and the k-nearest points (or neighbours) of training data are identified. Classification is then performed by the majority of the k-nearest neighbours, which correspond to a given event. The value of k is selected using cross-validation procedures.
Naïve Bayes (NB)	The NB classifier is based on the estimated conditional probabilities or likelihoods of the signal patterns available from each event. Given such likelihoods, the probability of a new unknown pattern having been generated by a specific event can be estimated directly. With a NB classifier, the input features are assumed to be independent of each other. With this assumption, it is possible to express the likelihood function for each event as the product of n simple probability density functions. Although the assumption of feature independence is often violated, the Bayesian approach is popular due to its simplicity and ease of implementation

Machine learning algorithms	Description
Support Vector Machine (SVM)	SVM algorithm is based on finding optimal separating decision hyperplanes between classes with the maximum margin between patterns of each class. Additionally, by using the so-called kernel functions, they can project the data from the original feature space they lie in, to another higher dimensional space. In this way, a linear separation in the new space becomes equivalent to a non-linear classification in the original space. An optimization technique is used to find the optimal separating hyperplanes that perform the required classifications

Chapter 2.

A comparison of fall detection algorithms (threshold-based vs. machine learning) using waist mounted tri-axial accelerometer signals from a comprehensive set of falls and non-fall trials

2.1. Abstract

Falls are the leading cause of injury-related morbidity and mortality among older adults. Over 30% of older adults fall at least once per year. Falls cause over 90% of hip and wrist fractures, and 60% of traumatic brain injuries in older adults. Another serious consequence of falls among older adults is the 'long-lie' experienced by individuals who are unable to get up and remain on the ground for an extended period of time after a fall. Considerable research has occurred over the past decade on the design of wearable sensor systems that can automatically detect falls and send an alert to care providers to reduce the frequency and severity of long-lies. The clinical utility of these systems depends on their sensitivity and specificity in distinguishing falls from activities of daily living (ADLs) and near-falls (loss-of-balance events followed by balance recovery). While most systems described to date incorporate threshold-based algorithms, machine learning algorithms may offer increased accuracy. In the current study, we compared the accuracy of these two approaches in detecting falls by conducting a comprehensive set of falling experiment with 10 young participants. Participants wore waist-mounted triaxial accelerometers and were trained to simulate the most common causes of falls observed in older adults, along with near-falls and activities of daily living. The overall performance of five supervised machine learning algorithms (Logistic Regression, Decision Tree, Naïve Bayes, K-Nearest Neighbour and Support Vector Machines) was greater than the performance of five threshold-based algorithms described in the literature, with SVM providing the highest combination of sensitivity (96%) and specificity (96%). While these

results are promising, further work is required to minimize false-positives, specifically associated with near-falls.

2.2. Introduction

Falls are the leading cause of injury-related hospitalization among older adults. Almost half of older adults who fall experience a minor injury, and up to 25% will experience a more serious injury such as a fracture [147]. A frequent and serious consequence of falls in seniors is the 'long-lie', where the faller is unable to get up on his own and remains helpless on the ground. Vellas et al. [56] reported that 70% of older adults who had fallen at home were unable to get up unaided, and more than 20% of patients admitted to hospital as a result of a fall had been on the ground for an hour or more. Tinetti et al. [47] found that 47% of non-injured fallers were unable to rise from the floor without assistance. Fall related long-lies among older adults are associated with pneumonia, dehydration, hypothermia, and high mortality rates, and contribute to fear of falling and social isolation [51, 53, 54]. Half of elderly people who experienced a long-lie (for an hour or more) passed away within 6 months, even if no direct injury occurred from the fall [55].

Over the past decade, there has been a great deal of research examining the role of wearable accelerometers and/ or gyros for automatic detection of falls [102-104, 106-108, 110, 112, 119, 148-150]. The goal of these systems is to reduce the frequency and consequences of long-lies, by quickly and accurately detecting the occurrence of a fall and alerting care providers to these events. While the cost and size of these sensors is rapidly decreasing, we are still at an early stage in the development of sensor systems (hardware and software combinations) that provide adequate sensitivity (ability to detect actual falls) and specificity (ability to avoid false-positives, which could desensitize the recipient of a fall alarm signal).

Research to date has focused primarily on testing the accuracy of these systems with datasets gathered from young adults who simulate falls onto padded mattresses in the laboratory environment, and wear the system while performing activities of daily living (ADLs). For example, Bourke et al. [102, 106] used signals from tri-axial

accelerometers mounted at the trunk and thigh to distinguish falls from ADLs. They proposed an Upper-Fall-Threshold (UFT) and Lower-Fall-Threshold (LFT) in an attempt to optimize the balance of false-positives and false-negatives. The UFT showed 100% sensitivity and 100% specificity, while the LFT provided 100% sensitivity and 91% specificity. Similarly, Kangas et al. [112] attached a tri-axial accelerometer at the waist, wrist and head of volunteers who performed simulated falls and ADLs in the laboratory. Their algorithms considered the pre-impact, impact, and post-impact phases of the fall, separately and in combination, and achieved up to 100% specificity and 95% sensitivity, based on a single sensor mounted at the waist.

The current study was designed to address three important limitations to previous measures of the accuracy of sensor systems in fall detection. First, laboratory simulations have not been based on existing evidence of the most common scenarios leading to falls in older adults. Second, previous studies have not considered near-fall events, along with ADLs, as a potential cause of false-positives. Third, studies have not directly compared the accuracy of machine learning versus threshold-based approaches for detecting falls.

To address this goal, we examined a library of video sequences of 227 real-world falls experienced by 130 older adults, collected as part of an ongoing project by our research team to study the mechanism of falls in long-term-care facilities [81]. Based on this video evidence, we simulated the 7 most common types of falls, along with 5 types of near-falls and 8 ADLs in laboratory experiments with young adults wearing tri-axial accelerometers. We then compared the accuracy in distinguishing falls from near falls and ADLs of previously published threshold-based algorithms by Bourke et al. [102, 106] and Kangas et al. [112] to five novel machine learning-based fall detection algorithms.

2.3. Material and methods

2.3.1. Participants

Ten healthy young adults participated in this study, ranging in age from 22 to 32 years (mean = 26.6 years, SD = 2.8 years). All participants were students at Simon

Fraser University, recruited through advertisements and flyers on university notice boards. The experiment protocol was approved by the Research Ethics Committee at Simon Fraser University and all participants provided informed written consent.

2.3.2. Experimental design

Our laboratory recently described [81] the most common causes of imbalance and activities associated with falls in older adults in long-term care, based on collection and analysis of video sequences of 227 real-life falls experienced by 130 older adults (of mean age 78 years, SD = 10). We found that 86% of falls were collectively due to incorrect shift of bodyweight (41%), trip (21%), hit/ bump (11%), collapse/ loss of conscious (10%) and slip (3%) Common causes of incorrect shifting of bodyweight included missteps or cross-steps during walking, imbalance when rising from a chair, and imbalance while descending from standing to sitting.

Our experimental design (Figure 2.1) included the above seven types of falls, along with five types of near-falls and eight ADLs. In near-fall trials, participants successfully recovered balance after experiencing slipping, tripping, hit or bump, imbalance due to a misstep or cross-step, and imbalance while rising from a chair. For ADLs, we included normal walking, standing quietly, rising from sitting, descending from standing to sitting, descending from standing to lying, picking up an object from the ground, ascending stairs and descending stairs. In the experimental design, equal weight was given to each fall and non-fall scenario by having each participant simulate 3 repeated trials for each category, resulting in 210 falls, 150 near-falls and 240 ADLs. For fall classification, near-falls and ADLs were combined into a ‘non-falls’ category.

2.3.3. Experiment protocol: Simulation of falls, near-falls and ADLs

During all fall and near-fall trials, the floor was covered with a 30 cm thick gymnasium mattress of the type used to cushion falls in athletic activities, such as high jumps. We also inserted a 13 cm top layer of high density ethylene vinyl acetate foam, so the composite structure was stiff enough to allow for stable standing and walking, but soft enough to reduce the forces during impact to a safe level. We also conducted

training sessions with each participant, where we displayed one representative video for each real-life fall and instructed participants to fall in a fashion similar to that observed in the older adult in the video [151, 152]. For simulating near-fall and ADL events, we did not present participants with videos, but instructed them to execute non-fall scenarios as if there were frailer older adults.

In slipping trials, participants were instructed to walk up to a carpet placed over the gym mat. They were then made to slip by rapidly translating the carpet from underneath their feet. In some trials, they were instructed to recover balance, while in others, they were asked to fall onto the gym mat. In tripping trials, participants were instructed to walk over the surface of the gym mat while wearing a tether at their ankle, that suddenly became taught (and then released). Again, in some trials, participants were instructed to recover balance, while in others they were instructed to fall onto the gym mat. During misstep/ cross-step trials, participants walked forward with high variability in their step width, and then took a narrow step or cross-step that caused loss of balance, followed by balance recovery or a fall. In rising from a chair trials, participants rose from sitting, then lost balance, and followed through by either recovering balance or falling onto the mat. In incorrect shift of bodyweight while descending from standing to sitting trials, participants missed sitting on a chair by glancing off the side, followed by a fall. In hit/ bump trials, the investigator applied a sudden sideways force to the trunk of the participant (at the level of the T1 vertebrae) followed by balance recovery or a fall. Finally, loss of consciousness or collapse trials were simulated from an initial standing position with the participant acting out the "legs giving way" or a “collapse” by falling straight down. Trials that resulted in successful balance recovery were categorized as ‘near-fall’ events, while trials that resulted in falls were categorized as ‘fall’ events. For fall trials, with the exception of loss of consciousness or collapse (where participants were asked to fall straight down), no instruction was provided on the fall direction.

2.3.4. Data acquisition

In each trial, we recorded body kinematics using an array of seven tri-axial accelerometers (range ±6 g, Opal model, APDM Inc., Portland, OR) mounted bilaterally

on the ankles and thighs, and at the anterior aspect of the waist, sternum and head. Data were recorded at 128 Hz for a duration of 15 s per trial and streamed directly to a computer for storage and subsequent analysis.

2.3.5. Data analysis

Classification using threshold-based algorithms

We examined the accuracy of five threshold-based algorithms on our data set. Each techniques has been previously evaluated for accuracy through laboratory-based fall simulations [102, 106, 112].

The BourkeUFT [102] algorithm was implemented by thresholding the vector sum (VS) of the tri-axial accelerometer signal attached at the waist. The minimum value of the peak VS at the time of impact from all fall data was taken as the Upper Fall Threshold (UFT). A fall was detected when the VS was over the UFT value.

The BourkeLFT [102] relies on the fact that the VS decreases during the descent phase of a fall (from its 1g value during perfectly quiet standing), and has a zero value during pure free-fall. The algorithm was implemented by evaluating the smallest value of the peak VS during the descent phase of falls (before impact). The smallest value of the VS during descent from all fall data was taken as the Lower Fall Threshold (LFT), and a fall was detected when the VS descended lower than the LFT value.

The Bourke4Phase [106] algorithm was based on detection of four distinct phases of the fall (pre-fall, critical, post-fall and recovery) and the VS exceeding both the LFT and UFT thresholds [153].

The Kangas2Phase [112] fall detection considers both the impact and post-impact phases of the fall, and utilizes tri-axial accelerometers placed at the wrist, waist or head. We implemented the Kangas2Phase algorithm using signals from the waist-mounted accelerometer. A fall was registered when the sliding VS threshold (set at 2g) was exceeded (in the impact phase) followed by confirmation of a lying posture two

seconds after impact. A lying posture was detected if the average acceleration in a 0.4 second time interval was 0.5 g or lower.

Finally, the Kangas3Phase [112] fall detection algorithm considers pre-fall, impact and post-fall posture recognition. As described by the authors, we detected the start of a fall when the VS went below 0.6g. We then recorded the peak VS over the subsequent 1000 ms (during impact). Finally, as in the Kangas2Phase1 algorithm, we detected a lying posture two seconds after impact, if the average acceleration in a 0.4 second time interval was 0.5 g or lower.

Classification using machine learning algorithms

We examine the accuracy of five machine learning techniques in distinguishing falls from non-falls with our dataset: Logistic Regression (LR), Decision Tree (DT), Naïve Bayes (NB), K-Nearest Neighbour (KNN) and Support Vector Machines (SVM). The feature vectors input to these routines were the means and variances of the X, Y and Z accelerations from each trial acquired from the waist-mounted accelerometer, over a 2.5 s time window centered around each fall, near-fall and ADL event (Figure. 2.2). The feature vector was then split into training and testing sets of equal size (i.e. 105 fall and 195 non-fall trials) by choosing data from the first five participants for training and the remaining five for testing. Furthermore, 10-fold cross-validation was performed with the training data, and model parameters were selected that yielded the best cross-validation accuracy. The final models were then trained on the entire training set from the 10 participants.

Comparison of threshold-based and machine learning-based algorithms

In comparing the accuracies of the two methods (threshold-based and machine learning), we divided our analysis into two parts. In the first part, the input parameters required for the threshold-based algorithms (e.g., UFT and LFT) were derived from data recorded from falls and non-falls performed by Participants 1-5. These algorithms were then tested on fall and non-fall data from the same five participants. This approach, where the algorithms are designed and tested on the same data, is identical to the approach used by previous authors [102, 106, 112]. To compare these results with the machine learning algorithms, we used the same data set (Participants 1-5) as the test

data set to calculate corresponding sensitivities and specificities. However, we trained each machine learning algorithm with fall and non-fall data recorded from Participant 6 - 10. This is an accepted rule for improved external validity of machine learning algorithms (that the training and learning data sets should be separate).

In the second part of the analysis, both our input parameter calculations and testing of threshold-based algorithms were conducted with data from Participants 6 -10. For machine learning algorithms, the roles of the training and test data sets from the 10 participants were reversed from their roles in part one. For each algorithm, we calculated sensitivities, specificities, false positive rates and false-negative rate as follows:

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{1}$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \tag{2}$$

$$False\ Positive\ rate = \frac{False\ Positive}{False\ Positive + True\ Negative} \tag{3}$$

$$False\ Negative\ rate = \frac{False\ Negative}{False\ Negative + True\ Positive} \tag{4}$$

We report average sensitivities and specificities of each classification algorithm from the two-part analysis. We also examined rates of false positive and false negative errors with detection error trade-off plots. All data analysis was performed in MATLAB (R2014a, The MathWorks Inc.).

2.4. Results

The overall sensitivity and specificity of five threshold-based and five machine learning algorithms are shown in Figure. 2.3. We found that all five machine learning algorithms provided sensitivities and specificities of at least 90%, while the sensitivities

and specificities for the threshold-based algorithms varied from 0% to 100%. Among the five machine learning algorithms, SVM provided the highest combination of sensitivity (96%) and specificity (96%) in distinguishing falls from non-falls. Among the threshold-based algorithms, Kangas3phase had the best classification with 94% sensitivity and 94% specificity.

Table 2.1 shows the number of trials, of the test set of 30 trials in each fall and non-fall category that were misclassified by each algorithm.

2.4.1. Missed falls

The number of false negatives (FNs) or missed falls by machine learning algorithms was spread across all seven types of fall. However, certain falls, such as, trips, collapse/ loss of conscious and ISBW due to a misstep resulted in 2 or less FNs by all five machine learning algorithms, whereas, slips (4 FNs by LR and 6 by DT), ISBW rising from a chair (4 FNs by KNN) and ISBW while descending (6 FNs by DT) were relatively more frequently missed. NB and SVM algorithms, which showed the highest sensitivity among all five machine learning algorithms caused least number of FNs (2 or less) in each of the seven types of falls. Among threshold-based algorithms, we found that BourkeUFT and BourkeLFT did not report any FNs in any of the seven fall categories. On the other hand, Bourke4Phase algorithm was the least effective in distinguishing falls and resulted a total of 64 FNs, with 6 or more FNs in each of the fall category with the exception of trips. Between the two Kangas' algorithms, Kangas3Phase was more effective and resulted in fewer FNs as follows: 4 FNs each in slips and ISBW while descending, 3 FNs in ISBW due to a misstep, 1 FN in each in trips and ISBW while rising from a chair. Two fall categories, hit/ bump and collapse/ loss of conscious did not result in any FNs at all by Kangas3Phase algorithm.

2.4.2. Near-falls as a cause of false positives

The number of false positives (FPs) due to near-falls by machine learning algorithms was also distributed across all five of the near-fall categories with no obvious trend. For example, with the exception of hip/ bump, at least one of the remaining four

near-fall categories resulted in at least 4 FPs for LR, NB, KNN and DT algorithms. Among machine learning algorithms SVM showed least number of FPs causing 3 or less false alarms in each of the five near-fall categories. For threshold-based algorithms, we found that while BourkeUFT and BourkeLFT were almost unable to make a distinction between near-falls and falls, the remaining three threshold-based algorithms showed relatively fewer number of FPs across all near-fall categories. Among these three algorithms, Bourke4phase resulted in the least number of FPs i.e. only 1 FP each in near-fall due to trips and hit/ bump.

2.4.3. ADLs as a cause of false positives

Two out of eight ADL categories caused FPs when analyzed by machine learning algorithms. Between the two, descending from standing to lying activity was more frequently misclassified and caused one or more false alarms by all machine learning algorithms with the exception of KNN. The second activity that was misclassified was picking an object from the ground, causing 6 FPs for NB and 2 FPs for DT. Among machine learning algorithms, KNN was found to be the most effective with zero FPs, followed by SVM and DT, which resulted in 2 FPs and 3 FPs respectively. For threshold-based algorithms, BourkeLFT was unable to differentiate between falls and ADL trials and misclassified all of the ADL trials and categories. For remaining four algorithms, descending stairs caused the most false alarms (9 FPs) followed by descending from standing to lying (5 FPs) and descending from standing to sitting (1 FP). Among five threshold-based algorithms, both Bourke4Phase and Kangas2Phase were the most effective algorithms and did not cause any false alarm for ADLs.

2.5. Discussion

In this study, we conducted laboratory-based experiments and recorded accelerations from waist-mounted sensors during simulation of common falling scenarios among older adults, along with ADLs and near-falls. We then evaluated the accuracy of five threshold-based and five machine learning algorithms in distinguishing falls from non-fall trials from waist acceleration data. We found that the best performing machine learning algorithm (SVM) provided 96% sensitivity and 96% specificity, while the best-

performing threshold-based algorithm (Kangas3Phase) provided 94% sensitivity and 94% specificity.

The sensitivities and specificities we found for threshold-based algorithms are substantially lower than what was reported previously. We also found that on our laboratory database, those threshold-based algorithms with the exception of Kangas3Phase, which provided high sensitivities (i.e. BourkeUFT and BourkeLFT) showed low specificities and vice versa. For example, Bourke4Phase algorithm proposed a set of fixed threshold values for features extracted form acceleration signals, and reported 100% sensitivity and specificity in distinguishing falls from non-falls [106]. However, when the same thresholds were applied to our dataset obtained from different participants and using different data collection strategies, the accuracy of Bourke4Phase algorithm dropped to 70% sensitivity and 99% specificity. This issue is mainly due to the threshold values set by the authors, which do not generalize well enough with different participants and data collection strategies. On the other hand, a fundamental goal of machine learning algorithms is to generalize a classification model beyond the examples in the training set. This is often achieved by optimizing the parameters of the machine learning algorithm through cross-validation using training data and then evaluated on the test-data unseen by the classification algorithm during model training. This procedure in machine learning algorithms ensures better external validity than threshold-based algorithm even if both algorithms provide same accuracy on a given dataset.

The threshold-based algorithms, which did not incorporate post-impact fall signal analysis, such as, BourkeUFT and BourkeLFT resulted in causing relatively greater number of false positives as opposed to the algorithms which did analyze the post impact phase of falls, such as, Kangas2Phase, Kangas3Phase and Bourke4Phase algorithms. The number of false alarms by Bourke4Phase and Kangas2Phase algorithms was even lower than what was provided by the five machine learning algorithms. Therefore, despite the fact that machine learning algorithms provided higher combinations of sensitivity and specificity than threshold-based algorithms, further improvement in results can be achieved either by training another classification model on the signals from post-impact fall phase or by designing a fusion algorithm, i.e.,

combining machine learning algorithm (for descend and impact phase fall analysis) and threshold-based algorithm (for post-impact fall phase analysis).

Accelerometers are key technology for wearable devices. We observed that 3D acceleration data provide important information about body movements from knowing its magnitude and orientation. For example, comparison of signals recorded during a backward fall due to slipping and a forward fall due to tripping is shown in Figure 2.2A. A slip was caused by sudden and fast movement of carpet from underneath the participant's feet resulting in posterior rotation of the trunk followed by a backward fall. Whereas, a trip resulted in anterior rotation of the trunk followed by a forward fall. The opposite polarity of the anterior-posterior (AP) acceleration signal after peak accelerations, confirms backward fall due to slip and forward fall due to trip. Similarly, Near-fall signals, in Figure 2.2B, represent successful balance recovery by a participant after his balance was perturbed. Note that the peak accelerations in near-fall trials were almost as high as falls, however, all three axes acceleration polarity remained unchanged, suggesting a successful balance recovery. Finally, Figure 2.2C shows acceleration signals from two ADLs. Picking an object from the ground involved forward bending down to reach an object placed at the floor and then rising up after retrieving that object. Note the AP-axis, where acceleration signal suggests a posterior rotation of the trunk followed by same amount of anterior rotation. All three axes had same pre and post ADL polarity suggesting that participant went back to his original posture. The second activity of descending from standing to lying involved gradual change of posture from initial standing to final lying on the floor. Note that while the acceleration signals show relatively low values, the final polarity of the acceleration has changed and is similar to what we observed in slip (backward) fall, suggesting that the participant was lying on his back. Hence, with appropriate signal processing, wearable accelerometers are a promising technology for identifying not only falls from non-falls but also the type or cause of falls, direction of falls, type and intensity of activity performed by participants undergoing monitoring.

Finally, we recognize the limitations of our study. Due to safety concerns, all fall trials were performed by young adults under controlled laboratory conditions and atop gymnasium mats. While there are important differences between falling patterns from

typical laboratory studies of young participants compared to real-life falls among older adults [81], we attempted to minimize these differences by conducting training sessions with each participant, where we displayed representative videos of real-life falls and instructed them to fall in a fashion similar to that observed in the older adult in the video. Furthermore, in order to minimize the effect of surface stiffness on falling behavior, the top 13 cm layer of the mats consisted of high-density ethylene vinyl acetate foam. This provided the composite structure with a stiffness high enough to allow for stable standing and walking, but soft enough to reduce impact forces to a safe level. Another limitation of the study was that in our laboratory experiment, we gave equal weight to each type of fall and non-fall category by recording 3 trials of them from every participant, whereas, in real-life, occurrences of certain type of falls and ADLs are more frequent than others. Similarly, fall detection problem in real-world has highly skewed dataset with a very small number of fall instances as oppose to ADLs. However, machine learning algorithms trained using such unbalanced datasets tend to generate trivial models that almost always predict the majority class [154]. Therefore, in order to balance different cost for false positive and false negative, we over-sampled the minority class by recording 210 fall trials and under-sampled the majority class by recording 390 non-fall trials (class ratio of 1:1.8).

In summary, we tested five machine learning and five threshold-based algorithms evaluated in this study, machine learning algorithms provided greater overall sensitivity and specificity. Among machine learning algorithms, SVM provided the greatest sensitivity and specificity of 96% in distinguishing falls from non-falls. Our results provide a template for further improvement of a robust fall detection system, which is necessary for the development of ‘smart’ personal emergency response system, which can automatically place a call for help in case of a fall to prevent long-lies. Future studies should also examine whether system accuracy in distinguishing falls from non-falls using machine learning algorithms can be improved through subsequent post-fall signal analysis or through different types of sensors (e.g. gyroscopes, blood pressure monitors or pressure sensors). Finally, the extent to which the accuracy of the results transfers to unexpected falls on hard surface by older adults will ultimately be addressed by testing the system with sensor signals obtained from older adults as they go about their daily activities.

Table 2.1. Number and type of false negatives and false positives resulting from each of the five threshold-based and machine learning algorithms

		Threshold Methods					Machine Learning				
		Bourke UFT	Bourke LFT	Bourke 4Phase	Kangas 2Phase	Kangas 3Phase	LR	NB	KNN	DT	SVM
False Negatives	**Falls**										
	Slip	00	00	08	06	04	04	01	02	06	02
	Trip	00	00	01	01	01	02	00	01	01	01
	Hit/ Bump	00	00	06	06	00	02	02	02	03	02
	Collapse	00	00	11	02	00	01	00	01	02	00
	ISBW_Misstep	00	00	11	08	03	01	00	01	00	01
	ISBW_Rising from a chair	00	00	13	07	01	01	00	04	03	01
	ISBW_Descending	00	00	14	00	04	00	00	02	06	01
False Positives	**Near-falls**										
	Slip	14	30	00	00	04	02	04	02	04	02
	Trip	17	30	10	03	08	01	06	04	04	03
	Hit/ Bump	18	30	10	01	01	02	03	02	02	02
	Collapse	12	30	00	01	04	04	04	04	02	03
	ISBW_Misstep	09	30	00	03	05	04	02	02	02	02
	ADLs										
	Normal walking	00	30	00	00	00	00	00	00	00	00
	Standing quietly	00	30	00	00	00	00	00	00	00	00
	Rising from a chair	00	30	00	00	00	00	00	00	00	00
	Descending from standing to sitting	01	30	00	00	00	00	00	00	00	00
	Descending from standing to lying	04	30	00	00	01	12	15	00	01	02
	Picking an object from the ground	00	30	00	00	00	06	00	00	02	00
	Ascending stairs	00	30	00	00	00	00	00	00	00	00
	Descending stairs	09	30	00	00	00	00	00	00	00	00

Notes: ISBW = incorrect shift of bodyweight; ADLs = activities of daily living; LR = Logistic Regression; NB = Naïve Bayes; KNN = K-Nearest Neighbour; DT = Decision Tree; SVM = Support Vector Machine.

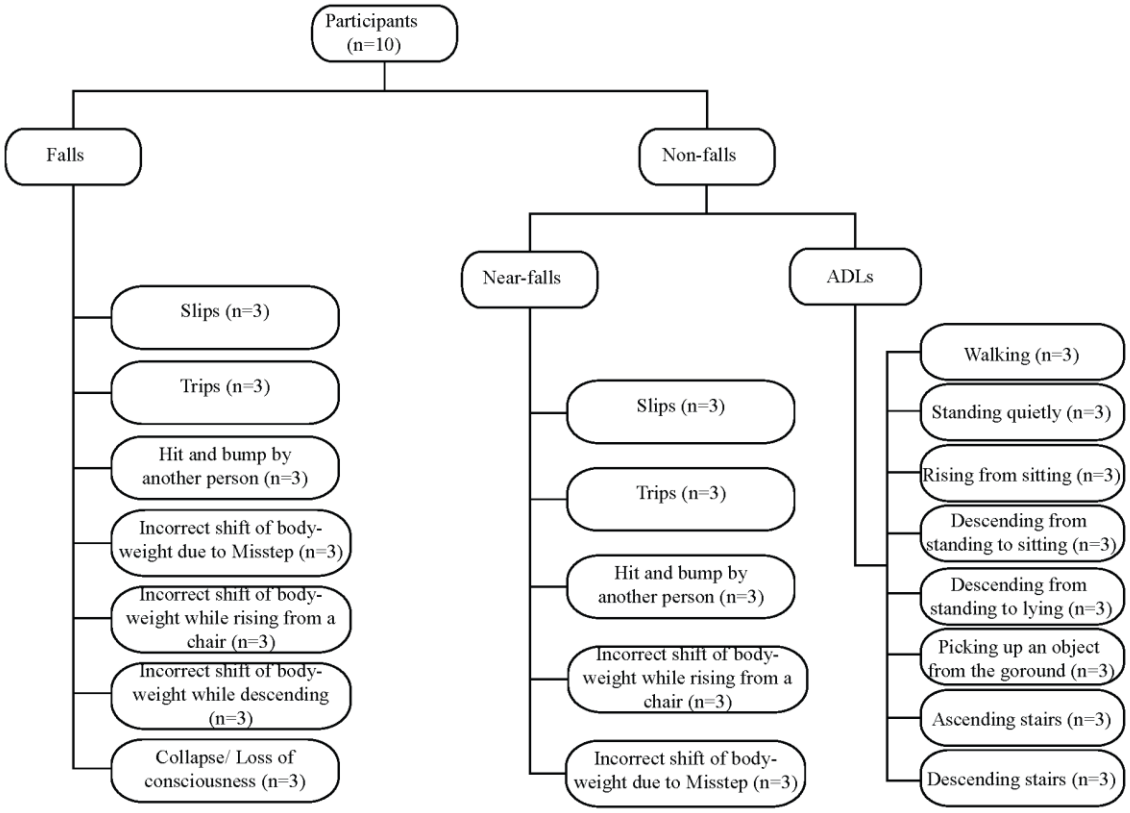

Figure 2.1. Experiment protocol, indicating the 7 types of falls, 5 near-falls and 8 activities of daily living (ADLs) simulated by each participant. Ten participants performed 3 repeated trials for each category, resulting in 210 falls, 150 near-falls and 240 ADLs. For fall classification, near-falls and ADLs were combined in the same 'non-falls' category.

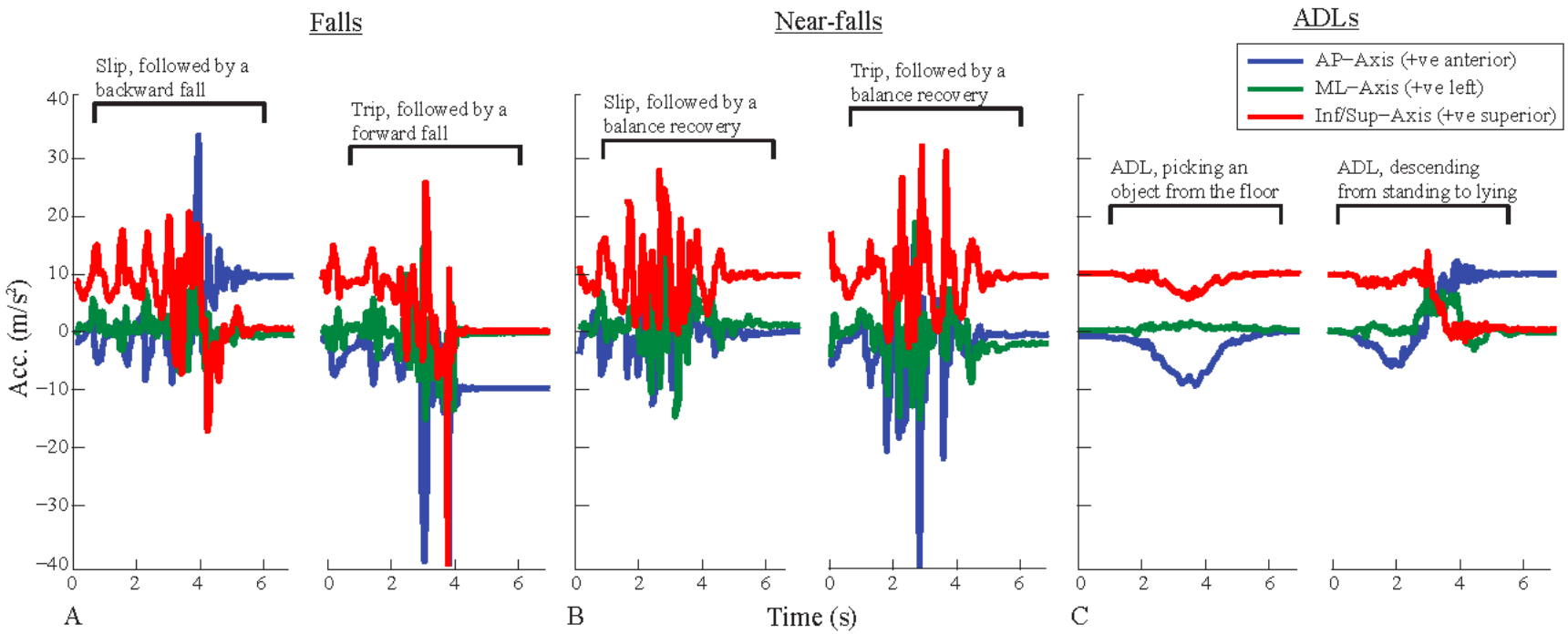

Figure 2.2. **Signals acquired from waist mounted tri-axial accelerometers from a typical participant during (a) falls, (b) near-falls, and (c) activities of daily living (ADLs). AP = acceleration in anterior/ posterior direction, ML = acceleration in medial/ lateral direction; Inf/Sup = acceleration in inferior/ superior direction.**

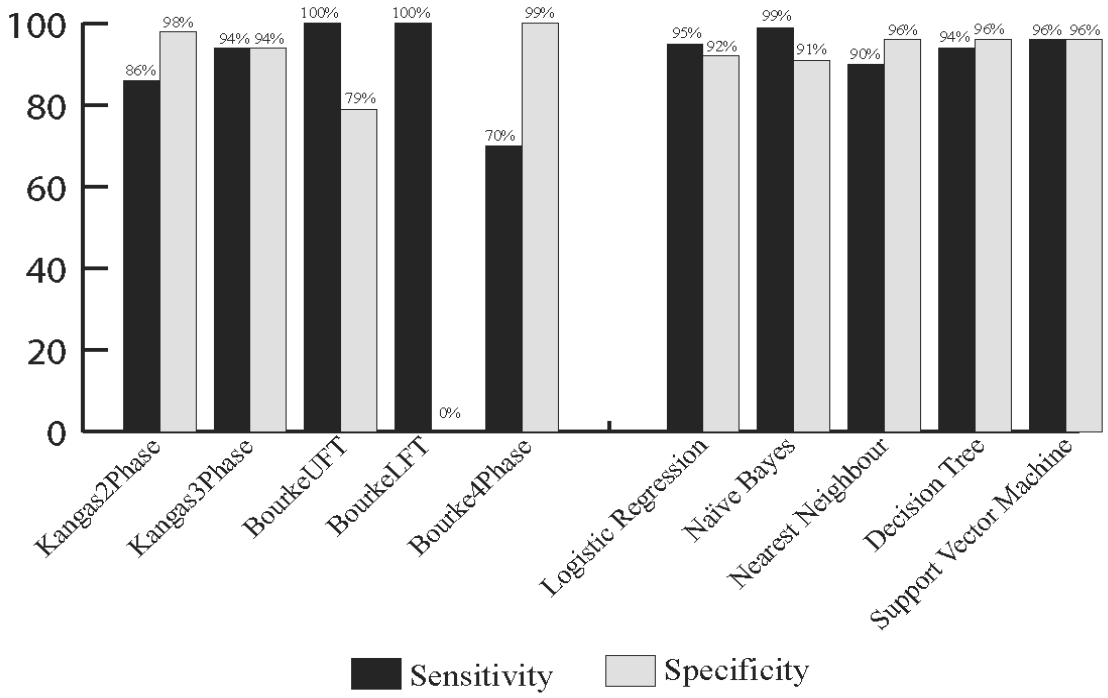

Figure 2.3. Comparison of sensitivity and specificity between five threshold-based and five machine learning algorithms in distinguishing falls from non-falls. Overall, the machine learning algorithms performed better than the threshold-based algorithms, with SVM providing the highest sensitivity and specificity of 96%.

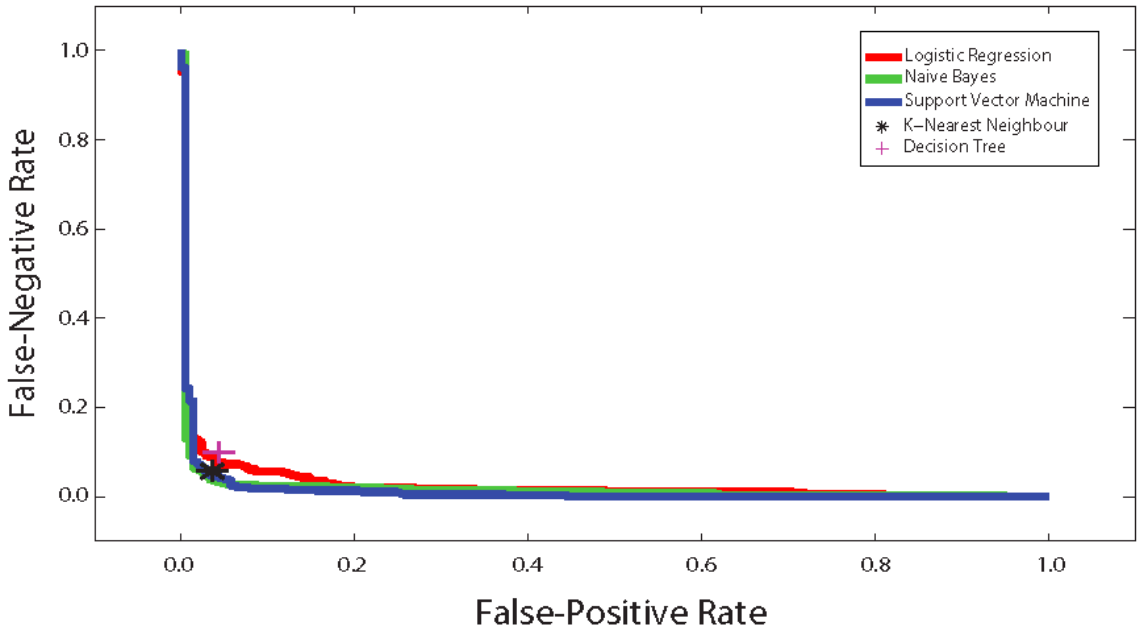

Figure 2.4. Detection error trade-off plot. False-positive rate and false-negative rate of five machine learning algorithms are plotted. All algorithms show similar performance.

Chapter 3.

Validation of accuracy of SVM-based fall detection system using real-world fall and non-fall datasets

3.1. Abstract

Falls are a major cause of injuries and deaths in older adults. Even when no injury occurs, about half of all older adults who fall are unable to get up without assistance. The extended period of lying on the floor often leads to medical complications, including muscle damage, dehydration, anxiety and fear of falling. Wearable sensor systems incorporating accelerometers and/ or gyroscopes are designed to prevent long lies by automatically detecting and alerting care providers to the occurrence of a fall. Research groups have reported up to 100% accuracy in detecting falls in experimental settings. However, there is a lack of studies examining accuracy in the real-world setting. In this study, we examined the accuracy of a fall detection system based on real-world fall and non-fall data sets. Five young adults and 19 older adults went about their daily activities while wearing tri-axial accelerometers. Older adults experienced 10 unanticipated falls during the data collection. Approximately, 400 hours of activities of daily living were recorded. We employed machine learning algorithm, Support Vector Machine (SVM) classifier to identify falls and non-fall events. We found that our system was able to detect 8 out of the 10 falls in older adults using signals from a single accelerometer (waist or sternum). Furthermore, our system did not report any false alarm during approximately 28.5 hours of recorded data from young adults. However, with older adults, the false positive rate among individuals ranged from 0 to 0.3 false alarms per hour.

3.2. Introduction

Falls are the number one cause of injuries and injury-related deaths in older adults [155, 156]. About half of older adults who fall are unable to get up without assistance, even when no injury occurs [49, 50]. The ensuing “long lie” on the floor often leads to dehydration, muscle damage, and fear of future falls.

Automatic fall detection systems based on wearable accelerometers and/ or gyros can reduce the risk for such ‘long lies, by detecting the fall and quickly alerting care providers of the event [106-108, 110, 117, 157]. The accuracy of these systems has traditionally been evaluated in laboratory simulations where young adults fall onto padded mattresses. For example, Diaz et al. [149] found that a system incorporating tri-axial accelerometers at the waist and a threshold-based fall detection algorithm was able to distinguish falls from activities of daily living (ADLs) with 100% sensitivity and 92.5% specificity. Kangas [112, 113] found that a threshold-based algorithm and tri-axial accelerometers at the waist or head provided up to 98% sensitivity in detecting falls. Bourke et al. [106] considered thresholds for velocity in the pre-impact phase, acceleration during impact, and body angle post-impact, and observed 100% sensitivity and 100% specificity in fall detection.

However, young adults falling in the laboratory setting may not simulate the movement patterns that are typical of falls in older adults [81]. The lack of evidence on the accuracy of wearable fall detection technology in older adults is a major barrier to refinement and uptake of this technology. We are aware of only one study that has measured the accuracy of wearable sensor systems in detecting falls in the real-life setting. Bagala et al. [133] evaluated 13 threshold-based fall detection methods on real-world data (including 29 falls in older adults), and found considerably lower sensitivity and specificity than the values reported in the simulated falls. The average sensitivity of the 13 methods was 57.0% (SD = 27.3%; maximum value=82.8%), and the number of false alarms generated during 1-day of monitoring ranged from 3 to 85.

We recently showed that machine learning approaches for interpreting signals from waist-mounted tri-axial accelerometers, specifically employing Support Vector Machine (SVM) data classification routines, are at least as accurate as threshold-based

techniques in distinguishing simulated falls from ADLs [158]. Similarly, Liu et al.[159] found that an SVM fall detection model, using data from a waist-mounted tri-axial accelerometer, provided promising rates of false positives (0.18 per hour for older adults) although the algorithm was not evaluated for sensitivity (since no falls occurred over the period of monitoring). Our goal in the current study was to test the accuracy of an SVM fall detection algorithm with signals from tri-axial accelerometers recorded from older adults during real-life falls and daily activities. We designed our Support Vector Machine (SVM) algorithm using data from simulated falls and non-fall trials acquired in the laboratory with young adults [158]. We then tested the system with real-life data from young healthy volunteers, and older adults in the long-term-care and acute care settings. We describe the of our SVM classifier in terms of sensitivity, specificity, and rates of false positives.

3.3. Material and methods

3.3.1. Real-world measures with young adults

Five young and healthy volunteers, ranging in age from 26 to 35 years (mean = 30.8 years, SD = 4.1 years) wore an array of seven tri-axial accelerometers (range ±6 g, Opal model, APDM Inc., Portland, OR) mounted bilaterally on the ankles and thighs, and at the waist, sternum and head. Approximately six daytime hours of time-stamped data were recorded from each participant who went about their normal everyday activities while wearing the sensors. A total of 28 hours and 38 minutes of data were recorded. None of the participants reported any fall during that time. The data collection was approved by the Research Ethics Committee at Simon Fraser University and all participants provided informed written consent.

3.3.2. Real-world measures with older adults at LTC

Nine older adults residing at New Vista long-term-care (LTC) facility in Burnaby, British Columbia were participants in sensor data collection. Participants ranged in age from 76 to 94 years (mean = 87.4 years, SD = 6.1 years. Each participant had experienced at least one fall (based on fall incident reports) during the past 12 months,

and were able to transfer independently to and from a bed or chair, and walk independently (with or without a walker or cane). Data were recorded from four tri-axial accelerometers (range ±6 g, Opal model, APDM Inc., Portland, OR) worn bilaterally on the ankles, and at the waist and sternum. A member of the research team placed the sensors on the participant every morning and removed them for recharging and data download at night before the individual went to bed. The researcher also stayed at the facility from morning until night, checking on the resident every 30 minutes and logging their activities.

A total of 214 hours of time-stamped sensor data were recorded from the nine participants over two months. During this time, one unintentional fall was recorded. The LTC facility was equipped with a network of 48 surveillance cameras installed in common areas for residents' safety. Members of our research team communicated daily with care providers and retrieved fall video footage, if any. Video footage of the fall occurring during sensor data collection was retrieved (Figure. 3.1). The experimental protocol was approved by the Research Ethics Committee at Simon Fraser University. In addition, all participants provided informed written consent for data collection using videos cameras and wearable sensors.

3.3.3. Real-world measures with older adults at acute care

Ten patients who ranged in age between 56 and 75 years (mean = 67.3 years, SD = 6.4 years), and had diagnosed progressive supranuclear palsy (PSP), participated in a cross-sectional study at the Robert Bosch Krankenhaus (RBK) Geriatrics Department in Stuttgart, Germany. The study examined clinical aspects of PSP and investigated the feasibility of audio-feedback to improve balance [160]. Data were recorded from each participants using a tri-axial accelerometer (range ±2 g, Dynaport MiniMod, McRoberts, The Hague, NL) mounted at the posterior aspect of the waist. From the ten patients, a total of 172 hours and 12 minutes of time-stamped sensor data were recorded. During this time, 9 real-world falls were reported. The occurrences of falls and their corresponding times were reported by the patients and/or their proxies, and were verified by research engineers through visual inspection of sensor signals at the reported times.

3.3.4. Data analysis

Data analysis focused on determining the accuracy of our SVM classifier, trained on laboratory data, in distinguishing falls from normal ADLs based on real-world fall and non-fall data.

Model training using laboratory data

An SVM model using a Radial Basis Function (RBF) kernel was trained [161] using data from 10 young adults. Participants wore the sensor system during laboratory experiments that simulated seven types of falls, selected to represent the most common falling scenarios (causes of imbalance and activities during falling) among older adults in long-term care [81]. Data were also acquired for a variety of near-falls and while the participant when about performing activities of daily living (ADLs). The details of the laboratory experiment protocol and how the falls and non-fall trials were simulated can be found in *section 2.3.3.*

3D acceleration signals recorded from fall and non-fall trials were used to calculate means and variances for each of the X, Y and Z axes over 2.5 s time window which resulted in a 6 dimension 'feature vector.' Furthermore, the two RBF kernel parameters C and γ were selected by a grid-search with exponential growing sequence (i.e. $C \in \{2^{-5}, 2^{-4}, \ldots, 2^{14}, 2^{15}\}$ and $\gamma \in \{2^{-15}, 2^{-14}, \ldots, 2^{2}, 2^{3}\}$). Each combination of parameters was tested with a 10-fold cross-validation, and the parameter combination with the best cross-validation accuracy was selected. The final model, used for classifying the real-world data, was then trained on the entire fall and non-fall data set from the 10 young adults.

Model testing using real-world data

The test data were obtained by calculating features (means and variances) of 3D acceleration signals recorded from 2.5-s consecutive time windows that overlapped by 1.5-s. Since data recorded in Stuttgart were from accelerometers with a range of ±2g, as opposed to the ±6g range employed for young and older adults in the Vancouver LTC facility, the features were normalized between 0 and 1 during both model training and

testing. Furthermore, three falls (apart from the above mentioned nine falls) captured at RBK geriatric department exceeded ±2g acceleration. The acceleration traces of these three falls showed the 'clipping effect' (or saturation) due to exceeding sensor acceleration range of ±2g. Since, this could affect the results of the analysis, the three falls that showed clipping effect were excluded from the analysis. To avoid multiple predictions of the same fall event, each time the classifier predicted a fall, a delay of 30 seconds was inserted before restarting the algorithm to consider the possibility of a subsequent fall.

Since the anatomical location of the sensors varied between the three participant sub-groups (young adults, older adults in Vancouver, and older adults in Stuttgart), we tested the fall detection accuracy of the trained SVM on each group separately. With young adults, data from each of the head, sternum and waist sensors were tested for fall detection. Each sensor was tested using a model trained from data recorded from the same sensor location during laboratory simulations. With residents at LTC facilities, the fall detection model was tested using the sternum accelerometer, since logistical issues impaired the collection of continuous data from the waist (several participants complained of discomfort during sitting and toileting, in which case care staff removed the waist sensors). With patients at RBK Geriatrics Department, waist mounted accelerometer data were tested for fall detection. The sensor was placed at the posterior aspect of the waist (likely contributing to greater comfort and compliance in wearing the device).

In evaluating each fall detection model, we focused on three measures of performance:

Sensitivity - the capacity of the system to detect falls and corresponds to the ratio of true positives to the total number of falls:

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (1)$$

Specificity - capacity of the system to avoid false alarms and corresponds to the ratio of true negatives to the total number of discarded trials:

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \quad (2)$$

Finally, the false positive rate - the number of false alarms per hour and corresponds to the ratio of the total number of false positives divided by the total recording time in hours:

$$False\ positive\ rate = \frac{False\ Positive}{ADL\ Time\ (in\ hours)} \quad (3)$$

All data analysis was performed using MATLAB (R2014a, The MathWorks Inc.).

3.4. Results

Our fall detection system showed perfect accuracy with all five young participants (Table 3.1). No false alarms were generated in the 28 hours and 38 minutes of recorded data. All three sensor-locations (head, sternum and waist) provided 100% specificity.

The system successfully detected the only fall occurred among the 9 residents of a Vancouver-area LTC facility during 214 hours of recorded sensor data (Table 3.2). During this time, a total of 10 false alarms were generated which corresponded to 0.05 false alarms per hour. At the individual level, no false alarms were generated with 3 residents, one alarm occurred in each of four residents, and two residents had 3 and 4 false alarms during approximately 17.5 hours and 14.5 hours of data recording respectively. The highest false positive rate was 0.27 for resident number 4.

For RBK Geriatric Department patients, the fall detection system successfully identified 7 out of 9 falls during 178 hours of recorded sensor data (Table 3.3). A total of 26 false positives were reported at the rate of 0.15 false alarms per hour. At the individual level, 4 or fewer false alarms were generated from 8 patients with half of those patients not having any false alarm. Two patients had 6 and 7 false alarms during approximately similar data recording time of 23.5 hours. The highest false positive rate

was recorded as 0.3 with patient number 1. Furthermore, the 2 falls missed by the algorithms were from the same patient (patient number 7).

3.5. Discussion

In the current study, we examined the accuracy of an accelerometer-based automatic fall detection algorithm in distinguishing falls in older adults. The algorithm incorporated an SVM machine learning algorithm that was trained using laboratory-based falls and non-fall data, and tested with sensor data acquired from real-life falls and during daily activities by older adults. We found that, with 3D acceleration data from a single sensor, our algorithm successfully detected 8 out of 10 real-world falls, and provided false positive rates from 0.05 to 0.15 false alarms per hour depending on the older adult dataset. This is comparable with the best performance reported by Bagala et al. [133] for 13 threshold-based fall detection algorithms (3 to 85 false alarms per 1-day monitoring of three participants).

Our approach diverged from traditional threshold-based fall detection methods to include advanced machine-learning techniques [158, 159], and this may account in part for the improved. Another likely source of the improvement is the data source used in training our fall detection algorithm. We designed our laboratory falling simulations to include the most common circumstances of real-life falls in older adults. Previous investigators have developed and evaluated their algorithms based on data from young subjects falling in the forward, backward and/ or sideways direction from a static, standing position. However, recent findings from our laboratory [81] have shown that approximately 48% of falls among older adults residing in long-term-care facilities occur while walking and 86% of the falls are collectively due to incorrect shift of bodyweight (41%), trip (21%), hit/ bump (11%), collapse/ loss of conscious (10%) and slip (3%). These falling scenarios are substantially different from the ones employed in the past for simulating falls in the laboratory environment. For each of these categories, we used video clips of actual falls among older adults to train young subjects to imitate the real-world fall. Furthermore, the incorporation of near-falls (imbalance episodes followed by successful balance recovery) along with ADL trials improved the quality of our experiment.

While our system performance appears to be comparable with the best threshold-based systems, further improvement is required to reduce the rate of false positives. The occurrence of false positives could have been due to the relatively similar number of non-fall trials and fall trials simulated in our laboratory experiments. The algorithm was trained with 210 falls and 390 non-fall trials. In everyday life, even among frail older adults, the proportion of time spent in performing normal activities greatly outweighs the time related to falls. Ideally, this distribution should be reflected in the data used for training a classification model. It is also possible that fall events exist in the data which were not reported (i.e., some false positives were actual falls) for participants recruited through the RBK Geriatrics Department, whose falls were self-reported. We expect the risk of missed falls to be lower for participants in LTC, where nursing staff are required to complete incident reports documenting all falls, and it is unlikely that falls are not identified and reported by care staff.

In summary, through acceleration data obtained from simulated falls by imitating the most common causes of falls of elderly people in long-term care facilities, we show that a robust fall detection algorithm can be designed for distinguishing real-world data into falls and non-falls. Finally, access to a robust data set is critical to the development of more accurate fall detection algorithms. Previous studies generally describe the tests performed and the results obtained, but sensor raw data are usually not publicly made available. The collection of real-life fall data is difficult and time-consuming, yet critical to algorithm testing. This points towards the need for shared databases of real-world fall and ADL data, available to the scientific community to design and test their fall detection algorithms.

Table 3.1. Fall detection performance indicators calculated from five young adults using support vector machine classifier

Participants	Recorded duration (hh:mm:ss)	Head			Sternum			Waist		
		Spec. (%)	False Pos. (n)	False Pos. rate (per hour)	Spec. (%)	False Pos. (n)	False Pos. rate (per hour)	Spec. (%)	False Pos. (n)	False Pos. rate (per hour)
Participant 1	6:15:10	100	00	00	100	00	00	100	00	00
Participant 2	5:09:51	100	00	00	100	00	00	100	00	00
Participant 3	4:57:57	100	00	00	100	00	00	100	00	00
Participant 4	5:52:18	100	00	00	100	00	00	100	00	00
Participant 5	6:23:01	100	00	00	100	00	00	100	00	00
Total	28:38:17	100	00	00	100	00	00	100	00	00

Notes: Spec. = Specificity; False Pos. = False Positive

Table 3.2. Fall detection performance indicators calculated using support vector machine classifier from nine older adults residing in LTC facility.

Participants	Recorded duration (hh:mm:ss)	Falls (n)	Sens. (n)	Spec. (n)	False Neg. (n)	False Pos. (n)	False Pos. rate (per hr)
Resident 1	83:37:11	01	100.00	100.00	00	00	0.00
Resident 2	28:34:43	00	n/a	99.99	n/a	01	0.03
Resident 3	17:38:28	00	n/a	99.99	n/a	02	0.11
Resident 4	14:37:58	00	n/a	99.99	n/a	04	0.27
Resident 5	5:32:54	00	n/a	100.00	n/a	00	0.00
Resident 6	26:25:41	00	n/a	99.99	n/a	01	0.04
Resident 7	18:15:20	00	n/a	100.00	n/a	00	0.00
Resident 8	12:06:01	00	n/a	99.99	n/a	01	0.08
Resident 9	7:11:59	00	n/a	99.99	n/a	01	0.14
Total	214:00:15	01	100	99.99	00	10	0.05

Notes: Sens. = Sensitivity; Spec. = Specificity; False Neg. = False Negative; False Pos. = False Positive.

Table 3.3. Fall detection performance indicators calculated from10patients at rbk geriatrics department using support vector machine classifier

Participants	Recorded duration (hh:mm:ss)	Reported falls (n)	Sens. (n)	Spec. (n)	False Neg. (n)	False Pos. (n)	False Pos. rate (per hr)
Patient 1	23:33:41	02	100	99.99	00	07	0.30
Patient 2	23:30:10	00	n/a	99.99	n/a	04	0.17
Patient 3	23:43:57	01	100	99.99	00	06	0.25
Patient 4	14:03:20	01	100	100.00	00	00	0.00
Patient 5	13:50:40	01	100	100.00	00	00	0.00
Patient 6	23:26:43	02	100	99.99	00	03	0.13
Patient 7	13:35:48	02	50	99.99	02	04	0.29
Patient 8	13:35:28	00	n/a	100.00	n/a	00	0.00
Patient 9	11:14:05	00	n/a	100.00	n/a	00	0.00
Patient 10	11:38:12	00	n/a	99.99	n/a	02	0.17
Total	172:12: 04	09	78	99.99	2	26	0.15

Notes: Sens. = RBK = Robert Bosch Krankenhaus; Sensitivity; Spec. = Specificity; False Neg. = False Negative; False Pos. = False Positive.

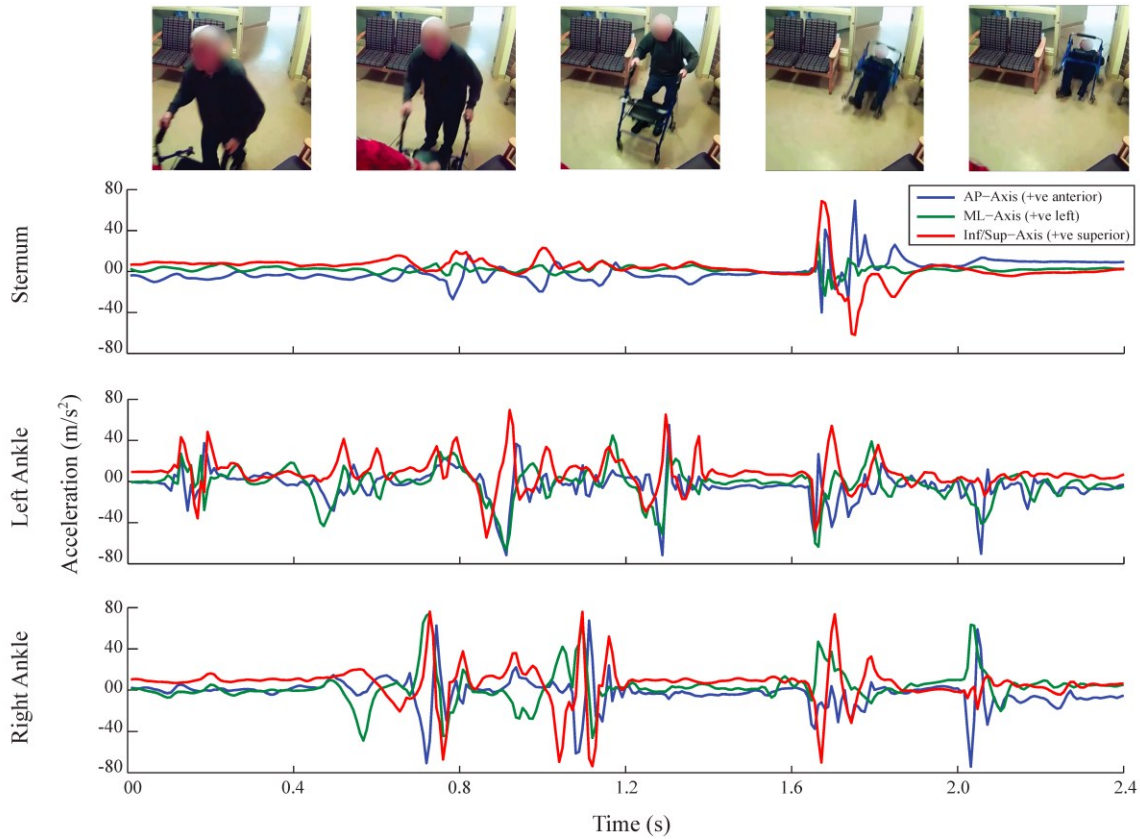

Figure 3.1. Sternum, left ankle and right ankle mounted tri-axial accelerometer signals in anterior/ posterior (AP), medial/ lateral (ML) and inferior/ superior (Inf/Sup) directions from a real-world backward fall recorded at a partner long-term-facility.

Chapter 4.

The effect of window size and lead time on pre-impact fall detection accuracy using support vector machine analysis of waist mounted inertial sensor data

4.1. Abstract

Falls are a major cause of death and morbidity in older adults. In recent years many researchers have examined the role of wearable inertial sensors (accelerometers and/or gyroscopes) to automatically detect falls. The primary goal of such fall monitors is to alert care providers of the fall event, who can then commence earlier treatment. Although such fall detection systems may reduce time until the arrival of medical assistance, they cannot help to prevent or reduce the severity of traumatic injury caused by the fall. In the current study, we extend the application of wearable inertial sensors beyond post- impact fall detection, by developing and evaluating the accuracy of a sensor system for detecting falls prior to the fall impact. We used support vector machine (SVM) analysis to classify 7 fall and 8 non-fall events. In particular, we focused on the effect of data window size and lead time on the accuracy of our pre- impact fall detection system using signals from a single waist sensor. We found that our system was able to detect fall events at between 0.0625-0.1875 s prior to the impact with at least 95% sensitivity and at least 90% specificity for window sizes between 0.125-1 s.

4.2. Introduction

Falls are the leading cause of injury among older adults in Canada, including over 90% of hip fractures [162, 163] and wrist fractures [164], and a large percentage of

head and spine injuries [165]. About 30% of older adults living in the community and 60% of individuals living in a residential care environment will experience at least one fall each year [166]. Hip fractures are the most significant injury related to falls, with approximately 23,000 annual cases in Canada, and medical costs in excess of $1 billion [7].

Wearable kinematic sensors such as accelerometers and gyroscopes represent a promising technology for preventing and mitigating the effects of falls in older adults. One of the key issues in preventing fall related injuries is to detect a fall in its descending phase with a sufficient lead time in order to deploy protective equipment (such as inflatable hip protectors, helmets, etc.) to cushion the fall prior to impact [167]. Wu and Xue [168] proposed a pre-impact fall detection technique by thresholding the vertical velocity profile of the waist worn accelerometer, and showed that with vertical velocity threshold set at -1 m/s their algorithm was able to detect all falls with at least 70 ms lead time with only three false positives found during approximately 13 hours of data. Similarly, Nyan et al. [121] showed 100% sensitivity with approximately 200 ms lead time by locating sensors at the sternum, waist and under the arm. However, Nyans threshold algorithm resulted in 16% of the activities of daily living (ADLs) being misclassified as falls.

Our study diverges from traditional threshold-based methods by using a machine learning pre-impact fall detection method – support vector machines (SVM) – for better adaptability and reliability. Furthermore, our study uses a wide variety of fall and daily activity scenarios to more rigorously test the accuracy of our SVM algorithm across a combination of varying lead times and window sizes, using a single waist mounted tri-axial accelerometer and gyroscope.

4.3. Methods

4.3.1. Participants

Ten healthy adults (ranging in age between 22 and 32 years) participated in the study. All participants were students at Simon Fraser University (SFU), recruited through

advertisements posted on university notice boards. All participants provided informed written consent and the experimental protocol was approved by the research and ethics committee at SFU.

4.3.2. Experiment design

We examined a library of video sequences of 227 real-life falls in older adults, acquired as part of an ongoing project by our research team to examine the mechanisms of falls in long-term care facilities [81]. We found that 75% of falls were collectively due to the following seven causes: (i) slips, (it) trips, (iii) hit or bump by an object or another person, (iv) collapse or loss of consciousness, (v) misstep or cross-step while walking and (vi-vii) incorrect shift of bodyweight while sitting down on or rising from a chair. We included all seven of these types of falls in our laboratory experiment. During all fall trials, the floor was covered with 30 cm thick gymnasium mats into which we inserted a 12 cm thick top layer of high-density ethylene acetate foam. The composite structure was stiff enough to allow for stable standing and walking while still soft enough to reduce the impact force to a safe level in case of a fall.

In addition to fall trials, eight activities of daily living (ADLs) were recorded which included: (i) walking, (ii) standing quietly, (iii) rising from sitting, descending from (iv) standing to sitting and from (v) standing to lying, (vi) picking up an object from the ground, (vii) ascending and (viii) descending stairs. All participants performed each fall and ADL category three times. Accordingly, over 10 participants, a total of 210 fall trials and 240 ADL trials were acquired.

4.3.3. Data acquisition

In each trial, we recorded body kinematics using a single tri-axial accelerometer and gyroscope (ranges of ±6 g and ±26.18 rad/s respectively, Opal model, APDM Inc., Portland, OR) worn on a belt at the anterior aspect of the waist. Data were recorded at 128 Hz for a duration of 15 s per trial and streamed directly to a computer for storage and subsequent analysis.

4.3.4. Data analysis

Our data analysis focused on determining how the various window size and lead time combinations influenced the ac- curacy of our pre-impact fall detection algorithm (Figure. 4.1).We used seventeen different data window sizes in combination with eighteen lead times to evaluate their effect on the sensitivity and specificity of the algorithm. The window sizes used varied from 0.125 s to 1.125 s with an increment of 0.0625 s, while the lead times varied from 0.0625 s to 1.125 s with the same increment.

In order to determine the base window location for fall trials, we estimated the instance of the body impacting the floor due to a fall by finding the time of peak resultant velocity from the waist sensor [3]. The resultant peak velocity was calculated through numerical integration of the high-pass filtered (cut-off frequency of 0.25 Hz to remove gravity signal) resultant acceleration signal. We then shifted the base window location a fixed amount back from the impact time point according to the chosen lead time (Figure.4.1a). For increasing window sizes, we shifted the start time point of the base window back in time by the corresponding amount.

For ADL trials, we visually identified the start and end time points of activity motion from the sensor signals, and then set the base window location at a random position within that time frame. ADL window start and end time points were shifted symmetrically from that base window as window sizes were increased. Lead times were not used in the analysis of ADL trials, as they do not contain a time point of interest analogous to the fall impact time.

Within each window we calculated the means and variances of X-, Y- and Z-axis accelerations, velocities and angular velocities to form the features for use in our Support Vector Machine (SVM) analysis (Figure 4.1b-d). We used the SVM implementation in LIBSVM [161] with a Radial Basis Function (RBF) kernel for pre-impact fall detection. The features (i.e. means and variances) were then split into training and testing sets of equal size by choosing the data from the first five participants for training and the following five for testing. The best combination of the two RBF kernel parameters C and γ was selected by a grid-search with exponential growing

sequences (i.e. $C \in \{2^{-5}, 2^{-4}, ..., 2^{14}, 2^{15}\}$; and $\gamma \in \{2^{-15}, 2^{-14}, ..., 2^{2}, 2^{3}\}$). Each combination of parameter choices was tested using a 10-fold cross-validation and the parameter with the best cross-validation accuracy was picked. The final model, which was used for classifying test data, was then trained on the entire training set using the selected parameters. The process of training and testing the SVM model was repeated for every combination of window size and lead time.

After creating classification sets of test data for all window size and lead time combinations, we evaluated algorithm performance by calculating the sensitivity and specificity of each classification set. To assess typical algorithm performance per trial, we calculated the mean and standard deviation of each trial's classification sensitivity (for fall trials) or specificity (for ADLs) across all combinations of window size and the three smallest lead times (0.0625-0.1875 s). All data analysis was performed in MATLAB (R2013a, The MathWorks Inc.).

4.4. Results

Overall sensitivity and specificity of trial classification for each combination of window size and lead time are shown in Figure 4.2. We found that our algorithm yielded relatively stable sensitivity and specificity values across all window sizes for the three smallest lead times between 0.0625-0.1875 s (Figure 4.2a), with sensitivity consistently above 95% and with specificity above 90% (for window sizes 1 s or smaller). For larger lead times (Figure 4.2b-f), sensitivity and specificity varied dramatically depending on window size, indicating algorithm performance was less robust for these cases.

Table 4.1 shows the individual trial means and standard deviations of classification sensitivity (for falls) and specificity (for ADLs), as calculated across combinations of all window sizes and the three smallest lead times. Our algorithm typically had very high classification sensitivity (means >97% and SDs <4%) for all fall trials, with the exception of incorrect transfer while rising from sitting (ITRS) which had a mean sensitivity of 93.5% and SD of 7.5%. Classification specificity for ADLs was very high (means >97% and SDs <4%) for rising from sitting to standing (RSS), descending from standing to sitting (DSS), and standing quietly (SQ); moderately high (means >94%

and SDs <5%) for normal walking (NW), ascending stairs (AS), and descending stairs (DS); but were relatively low and/or variable for descending from standing to laying (DSL, mean of 93.2% but SD of 9.1%) and picking up an object from the ground (POG, mean of 85.6% and SD of 11.3%).

4.5. Discussion

In this study we evaluated for the first time, to the best of our knowledge, the effect of data window size and lead time on pre-impact fall detection accuracy using data from a waist-mounted inertial sensor. Furthermore, we employed a machine learning algorithm (SVM), as opposed to traditional threshold based techniques, to allow for more adaptability and robustness across participant and motion variability.

Based on the analysis of data collected in lab experiments with young adults, our system provided at least 95% sensitivity and at least 90% specificity for combinations of window size from 0.125-1 s and lead time from 0.0625-0.1875 s. However, we found that for lead times 0.25 s or greater, sensitivity and specificity varied dramatically with choice of window size, indicating poor robustness of the classification performance. Therefore, we would recommend the use of a target lead time around 0.1875 s or less, and window size 1 s or less for robust pre-impact fall detection.

Furthermore, we believe our method of estimating the time of impact for fall trials, corresponding to the time of peak resultant linear velocity, is a more intuitively accurate method than peak acceleration methods used previously, as the largest accelerations would typically occur after impact [169].

There are several limitations of our study. Due to safety concerns, all fall and ADL trials were performed by young adults under controlled laboratory conditions and atop gymnasium mats. While there are important differences between falling patterns from typical laboratory studies of young participants compared to real-life falls among older adults [170], we attempted to minimize these differences by having our participants simulate a variety of falls most commonly observed among older adults [81]. Also, our analysis did not attempt to analyse sensor signals by sliding a sampling window along

the data stream, as would be necessary in a real-time implementation for triggering device deployment, however, our study design allowed for a controlled method of testing the effects of window size and lead time. Finally, our system provided relatively low overall specificity, likely due to our wide range of ADLs tested (with individual specificities ranging from 85.6%-100%) and a modest testing sample from five participants. Future work is required to compare the accuracy of machine learning versus threshold-based approaches on the same data set. While current performance is too low for practical use in device deployment, it may be improved in the future through the use of larger training datasets of falls and ADLs recorded from older adults, or with the use of complementary signals from other physiological sensors.

Our results provide a template for future development of a robust pre-impact fall detection system, which is necessary for the development of ‘smart’ next generation inflatable hip protectors or helmets for improved force attenuation and user acceptance.

Table 4.1. Individual trial means and standard deviations (sd) of classification sensitivity (falls) and specificity (ADLs)[a].

	Falls								ADLs							
	CS	**HB**	**ITDS**	**ITRS**	**LCC**	**slip**	**trip**		**NW**	**AS**	**DS**	**RSS**	**DSS**	**DSL**	**SQ**	**POG**
Sens	99.3%	100.0%	97.4%	93.5%	98.2%	99.3%	99.9%	**Spec**	94.5%	96.3%	94.6%	99.7%	97.8%	93.2%	100.0%	85.6%
SD	2.0%	0.0%	4.0%	7.5%	3.5%	2.4%	0.9%	**SD**	4.6%	4.7%	4.6%	1.3%	3.7%	9.1%	0.0%	11.3%

[a]Descriptive statistics calculated by including all combinations of window sizes from 0.125-1.125 s and lead times from 0.0625-0.125 s (0.0625 s increments), as shown in Fig. 4.2a. CS = cross-step, HB = hit or bumped, ITDS = incorrect transfer while descending from standing, ITRS = incorrect transfer while rising from sitting, LCC = loss of consciousness or motor control, NW = normal walking, AS = ascending stairs, DS = descending stairs, RSS = rising from sitting to standing, DSS = descending from standing to sitting, DSL = descending from standing to laying down, SQ = standing quietly, POG = picking up an object from the ground.

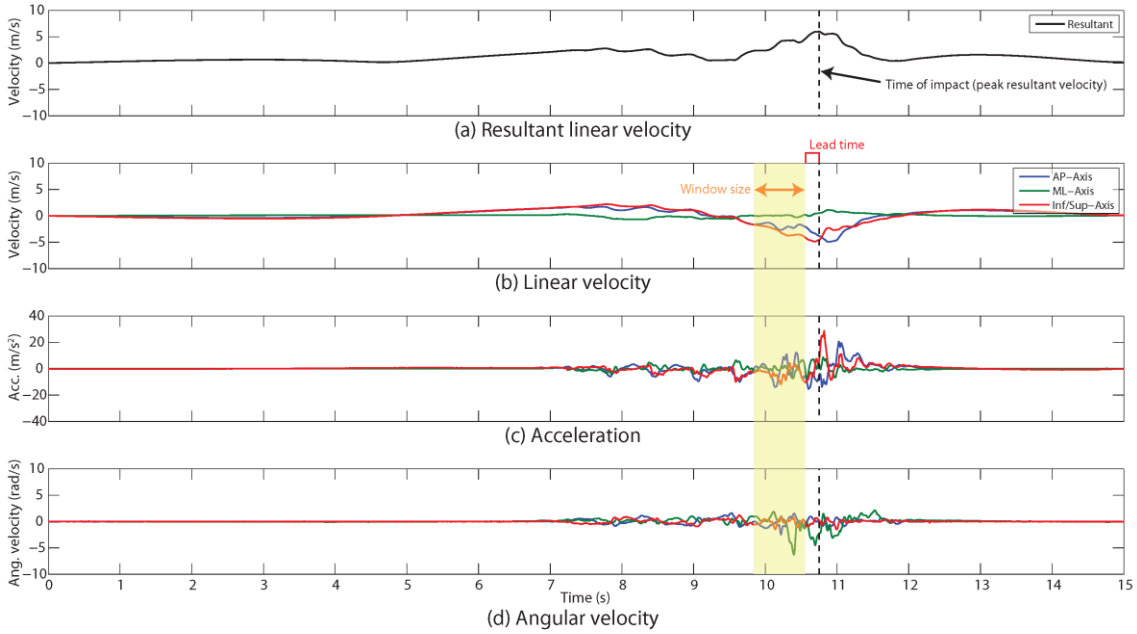

Figure 4.1. **Waist sensor signals for a sample slip fall trial. (a) Time of impact (dashed line) is estimated by finding the time of peak resultant linear velocity (obtained from numerical integration of the resultant acceleration signal), and the window location (yellow shading, not shown to scale) is shifted by the lead time (not shown to scale) ahead of the time of impact. Mean and variance features are calculated within the window for each of the anteroposterior (AP), mediolateral (ML), and inferior-superior (Inf/Sup) axes of the (b) linear velocity, (c) acceleration and (d) angular velocity signals. Note that the peak linear velocity does not always coincide with peak acceleration.**

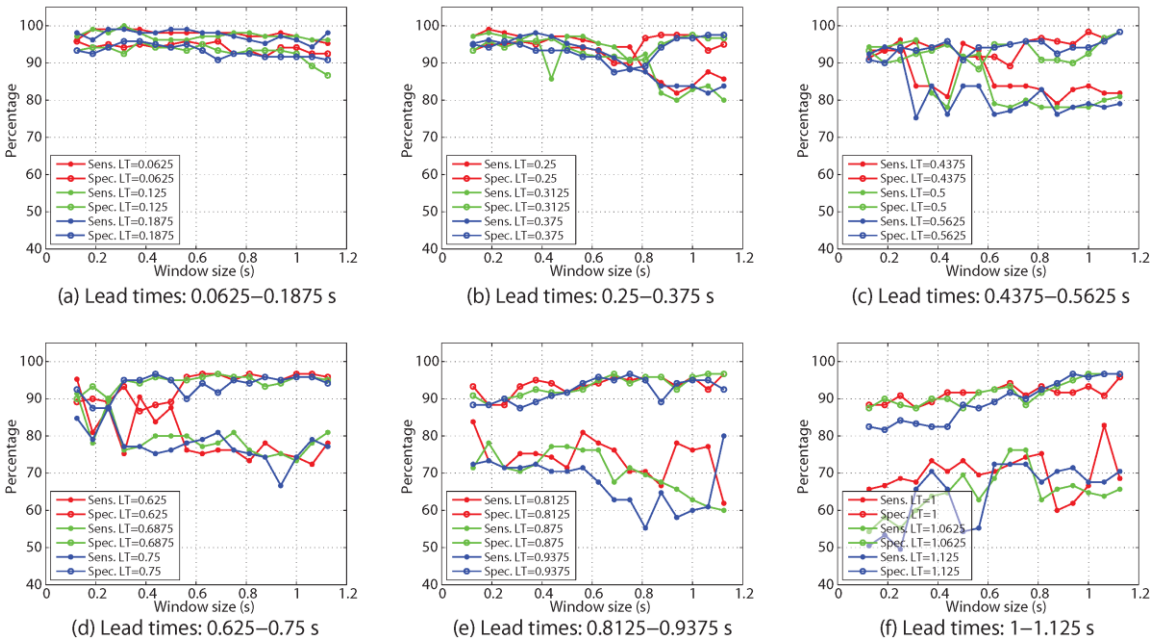

Figure 4.2. **Overall sensitivity and specificity of trial classification for each combination of window size and lead time. Subfigures (a-f) show results for triplets of increasing lead time size. Note that sensitivity and specificity are relatively stable across all window sizes for the three smallest lead times between 0.0625-0.1875 s (a), with sensitivity consistently above 95%. For larger lead times (b-f), sensitivity and specificity varied dramatically depending on window size, indicating the algorithm performance was less robust for these cases.**

Chapter 5.

Distinguishing near-falls from daily activities with wearable accelerometers and gyroscopes using support vector machines

5.1. Abstract

Falls are the number one cause of injury in older adults. An individual's risk for falls depends on his or her frequency of imbalance episodes, and ability to recover balance following these events. However, there is little direct evidence on the frequency and circumstances of imbalance episodes (near falls) in older adults. Currently, there is rapid growth in the development of wearable fall monitoring systems based on inertial sensors. The utility of these systems would be enhanced by the ability to detect near-falls. In the current study, we conducted laboratory experiments to determine how the number and location of wearable inertial sensors influences the accuracy of a machine learning algorithm in distinguishing near-falls from activities of daily living (ADLs).

5.2. Introduction

Falls are the leading cause of injuries in older adults with a substantial impact on health and healthcare costs. Approximately one in three persons over the age of 65 falls at least once each year [171-173]. An individual's risk for falls depends on his or her frequency of imbalance episodes, and ability to recover balance following these events [58, 174, 175]. For example, investigators have found that older adults who report multiple "near-falls" (missteps or stumbles) are more likely to go on to fall [176]. An accurate quantification of near- falls during daily activities could assist clinicians in assessing balance and developing strategies to prevent future falls [57, 176]. However,

our current knowledge of near-falls in older adults is based on self-reports, which are often unreliable and likely underestimate the true occurrence of such events [58, 177].

Wearable inertial sensors, such as miniature accelerometers and/ or gyroscopes represent a promising technology for objectively quantifying balance, mobility and falls in older adults. Sensor hardware is rapidly advancing in terms of size, accuracy and cost. However, challenges remain in developing software to derive accurate, reliable and clinically relevant outcomes from sensor data. At present, the primary application for these systems is to detect the occurrence of a fall and alert care providers to this event [119, 121, 173].

Our goal is to enhance the utility of wearable fall monitoring systems beyond fall detection, to distinguish near-falls from activities of daily living (ADLs). In particular, the current paper describes efforts to test, through laboratory experiments, how the number and location of sensors (3D accelerometers and gyros) influence the accuracy of a machine learning algorithm in distinguishing near-falls from ADLs.

5.3. Methodology

5.3.1. Participants

Ten healthy adults (ranging in age between 22 and 32 years) participated in the study. All participants were students at Simon Fraser University (SFU), recruited through advertisements posted on university notice boards. All participants provided informed written consent and the experimental protocol was approved by the research and ethics committee at SFU.

5.3.2. Experiment design

During the experiment, participants underwent five types of near-falls and eight different activities of daily living (ADLs) (Figure 5.1). These near-fall scenarios were selected as being representative of those emerging as most common from a study analyzing video-captured real life falls in long term care. All participants viewed falls from

this library were then asked to act out the scenarios [152]. All near-fall trials were performed on a 30 cm thick gymnasium mattress, into which we inserted a 13 cm top layer of high density ethylene vinyl acetate foam so the composite structure was stiff enough to allow for stable standing and walking, but soft enough to reduce the impact force to a safe level in case of a fall. In the near-falls, the participants were subjected to five different scenarios: (i) slips, (ii) trips, (iii) incorrect transfer while rising from sitting to standing (iv) misstep while walking, and (v) hit and bump by another person. For ADLs, eight scenarios were included: (i) walking, (ii) standing quietly, (iii) rising from sitting, descending from (iv) standing to sitting and (v) standing to lying, (vi) picking up an object from the ground, (vii) ascending and (viii) descending stairs. All participants performed three trials in each category. Accordingly, with 10 participants, a total of 150 near-falls and 240 ADLs were recorded.

5.3.3. Data acquisition

In each trial, we used seven inertial sensors (triaxial accelerometers having a rage of ±6 g and triaxial gyroscopes having a range of ±1500 deg/s, Opal model, APDM Inc., Portland, OR) worn bilaterally on ankles and thighs, and at the waist, sternum and head recording at 128 Hz to acquire synchronized measures of the 3D accelerations and angular velocities.

5.3.4. Data analysis

Data analysis focused on determining how the number and location of sensors influenced the ability of our classification algorithm to distinguish near-falls from ADLs. In the single sensor category, head, sternum, waist and both thigh sensors were included but not right or left ankle, based on the consideration that asymmetry in foot movements could necessitate bilateral placement in any real life application of our sensor technology. Moreover, in all three or more sensor categories, only one of the thigh sensors (i.e. right thigh) was used in the analysis. Thigh sensors are particularly useful for identifying transitions in movement, for example, descending from standing to sitting or lying position and vice versa, and one thigh sensor is deemed sufficient to capture such transition movements [111].

For each trial, we identified the approximate instant of fall-arrest (for near-fall trials) and activity completion (for ADL trials) by visual inspection of the sensor data. We then selected a 2.5 s time window prior to this instant to calculate the means and variances of the X, Y and Z signals for each accelerometer and gyroscope sufficient to capture the near- fall event from the initiation to arrest phase (Figure 5.2).

We used the Support Vector Machine (SVM) implementation in LIBSVM [161] with Radial Basis Function (RBF) kernel to distinguish near-falls from ADLs. The features (i.e. means and variances) were then split into training and testing sets of equal size by choosing the data from the first five participants for training and the following five for testing. The SVM constructs a hyper-plane or a set of hyper-planes in a high or infinite-dimensional space, which can be used for classification. However, the effectiveness of the SVM depends on the selection of kernel and the kernel's parameters. In this study we used SVMs with RBF kernel which required two parameters C and γ. The best combination of C and γ was selected by a grid search with exponential growing sequence of C and γ (i.e. $C \in \{2^{-5}, 2^{-4}, ..., 2^{14}, 2^{15}\}$; and $\gamma \in \{2^{-15}, 2^{-14}, ..., 2^{2}, 2^{3}\}$). Each combination of parameter choices was checked using a 10-fold cross-validation and the parameter with the best cross-validation accuracy was picked. The final model, which was used for classifying test data, was then trained on the whole training set using the selected parameters. The procedure was conducted on the data from each sensor, and for each possible combination of 2, 3, 4, 5 and 6 sensors. In each case, we then calculated the sensitivity and specificity as:

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{8}$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \tag{9}$$

All data analysis was performed in MATLAB (R2013a, The MathWorks Inc.).

5.4. Results

We found that our SVM algorithm showed good sensitivity and specificity in distinguishing near-falls from ADLs with various sensor combinations (Table 5.1). With a single sensor, the sensitivity and specificity of the system was at least 88% except for the waist sensor, which had 80% sensitivity.

With two sensors, the least number of false positives (FP) and false negatives (FN) was provided by the left ankle + right ankle combination, which distinguished near-falls and ADLs with 96% sensitivity and 98% specificity.

With three sensors, the highest sensitivity and specificity was provided by (a) left foot + right foot + sternum and (b) left foot + right foot + waist. Both combinations showed 100% sensitivity and 99% specificity.

The best overall performance was observed with the five sensor combination of left foot + right foot + right thigh + waist + head, which did not result in any false positive or false negative, and provided 100% sensitivity and specificity in distinguishing near-falls and ADLs. Sensitivity and specificity were no better with four and six sensor combinations than with three.

5.5. Discussion

In this study, we conducted lab based experimental trials with young adults to examine the utility of a wearable sensor array for distinguishing near-falls from ADLs. Our results indicated that the data from various combinations of three or more sensors, when input in our Support Vector Machine algorithm, provided sensitivity and specificity higher than 99% in distinguishing near-falls from ADLs. We also found that sensor placement at the feet considerably decreased false negatives indicating that lower extremity body kinematics was essential to identify near-falls.

There are important limitations to this study. First, our participants were healthy young adults, and they were aware of the external perturbations being applied to disturb

their balance. An important unanswered question is the extent to which our classification procedure and results will transfer to unexpected near-falls in real-life scenarios by older adults, including those with specific disease conditions or neuromuscular impairment. Ultimately, this issue can only be addressed by testing the system with older adults as they go about their daily activities. However, several aspects of our experimental design enhance the validity of our results for older adults. Most importantly, before commencing a given series of trials, each of our participants studied representative video clips of real-life falls experienced by older adults residing in long-term care, and were instructed to "act out" a similar fall and near-fall [152]. Despite the inevitable variability in the acting style of participants, we believe this approach substantially enhanced the validity of our results for older adults. Second, given the current size of self-contained wearable 3D sensors with on-board data storage and power supply (which are at least the size of large wrist watches), there is a legitimate concern that routine wear may be met with low user compliance in the target population. However, given the rapid rate of miniaturization of these components, one might expect that sufficient performance will soon be achieved with units the size of small plasters.

This study demonstrates the utility of a wearable sensor system in distinguishing near-falls from ADLs with high accuracy. Incorporation of this application in fall monitoring systems should substantially enhance their utility for health professionals in assessing and monitoring the effectiveness of strategies in reducing fall risk.

Table 5.1. Sensitivity and specificity of 3d accelerometer and rate-gyro arrays in separating near-falls from activities of daily living

Sensor Combination	No. of FP	No. of FN	Sens.	Spec.
Single sensor				
Head	11	07	90.66	90.83
Sternum	06	09	88.00	95.00
Waist	05	15	80.00	95.83
L.thigh	11	03	96.00	90.83
R.thigh	01	06	92.00	99.16
Two sensors				
L.foot+R.foot	02	03	96.00	98.33
L.thigh+R.thigh	07	02	97.33	94.16
R.thigh+Waist	00	18	76.00	100.00
R.thigh+Sternum	01	12	84.00	99.16
R.thigh+Head	03	12	84.00	97.50
Waist+Sternum	03	07	90.66	97.50
Waist+Head	06	20	73.33	95.00
Sternum+Head	05	11	85.33	95.83
Three sensors				
L.foot+R.Foot+R.thigh	01	03	96.00	99.16
L.foot+R.foot+Waist	01	00	100.00	99.16
L.foot+R.foot+Sternum	01	00	100.00	99.16
L.foot+R.foot+Head	05	02	97.33	95.83
R.thigh+Waist+Sternum	01	10	86.66	99.16
R.thigh+Waist+Head	02	18	76.00	98.33
R.thigh+Sternum+Head	03	07	90.66	97.50
Four sensors				
L.foot+R.Foot+R.thigh+Waist	01	02	97.33	99.16
L.foot+R.Foot+R.thigh+Sternum	01	01	98.66	99.16
L.foot+R.Foot+R.thigh+Head	01	00	100.00	99.16
L.foot+R.Foot+Waist+Sternum	01	00	100.00	99.16
L.foot+R.Foot+Waist+Head	02	00	100.00	98.33
L.foot+R.Foot+Sternum+Head	01	00	100.00	99.16
R.thigh+Waist+Sternum+Head	02	20	73.33	98.33
Five sensors				
L.foot+R.Foot+R.thigh+Waist+Sternum	01	01	98.66	99.16

Sensor Combination	No. of FP	No. of FN	Sens.	Spec.
L.foot+R.Foot+R.thigh+Waist+Head	00	00	100.00	100.00
L.foot+R.Foot+R.thigh+Sternum+Head	01	01	98.66	99.16
Six sensors				
L.foot+R.Foot+R.thigh+Waist+Sternum+Head	02	01	98.66	98.33

False Positive (FP) = ADLs, incorrectly identified as near-falls
False Negatives (FN) = Near-falls, incorrectly identified as ADLs.
Sens. = Sensitivity
Spec. = Specificity.

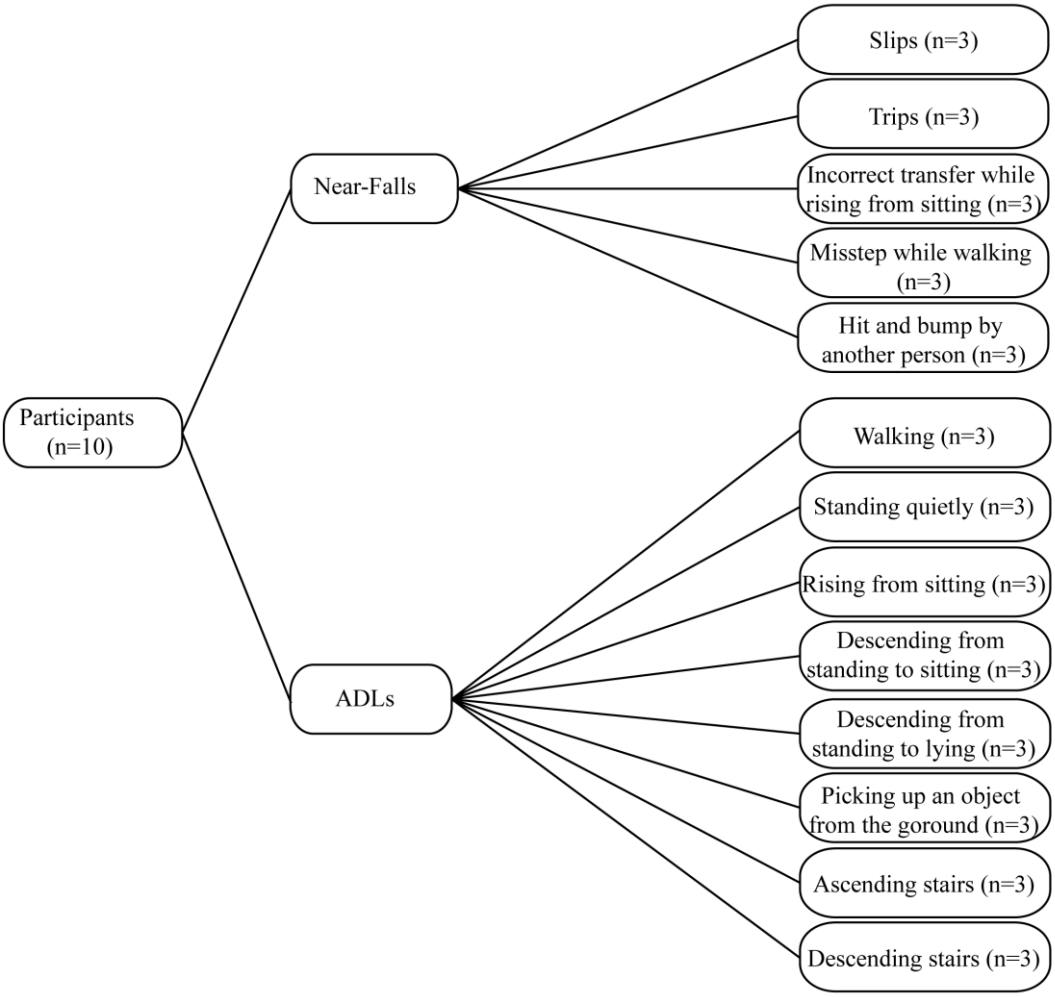

Figure 5.1. Experiment protocol, indicating various types of near-falls and Activities of Daily Living (ADLs) simulated by each participant.

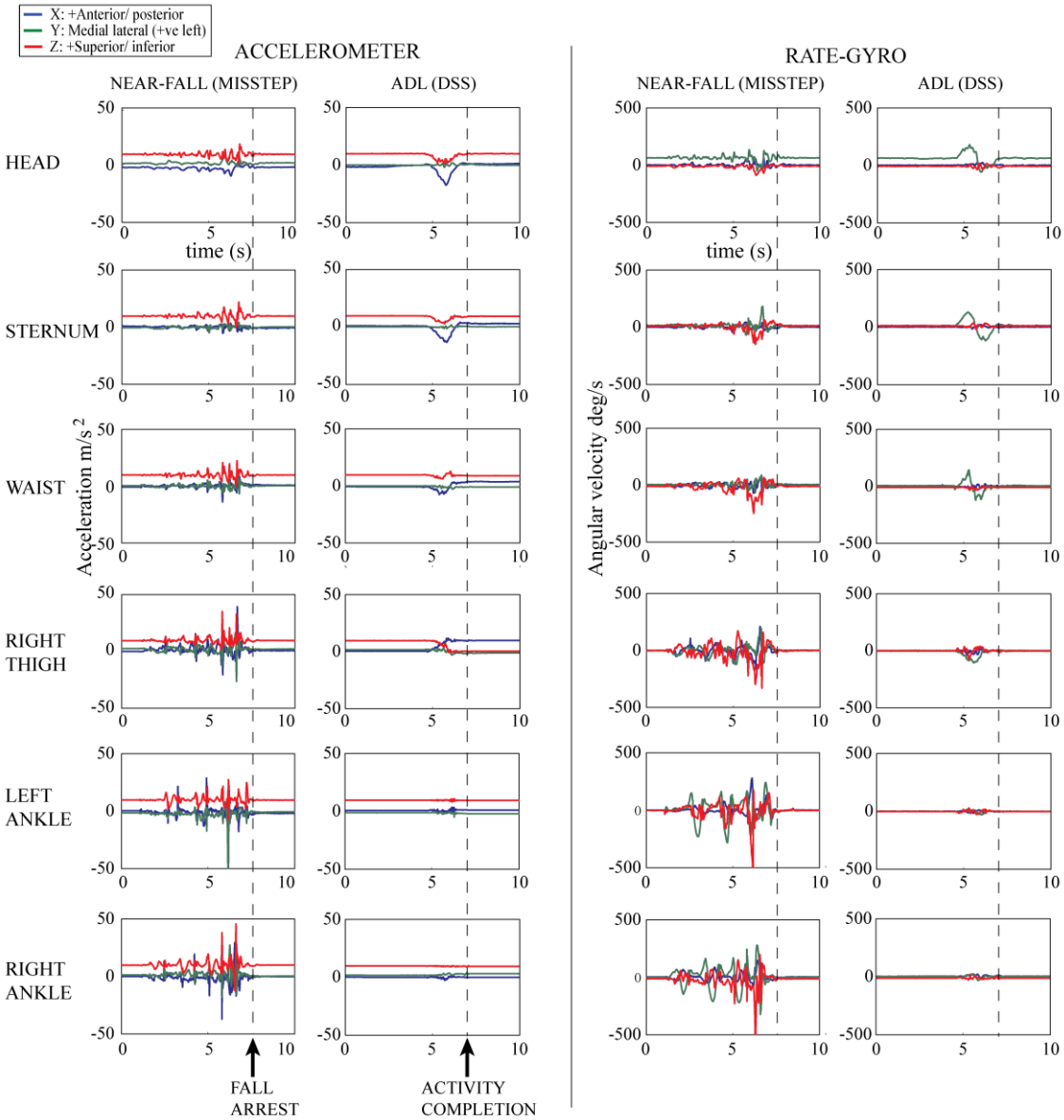

Figure 5.2. **Acceleration and rate-gyro traces in X, Y and Z direction from a typical participant in near-fall (Incorrect Transfer while Rising from Sitting (ITRS)) and ADL (Descending from Standing to Sitting (DSS)). The two vertical dotted lines show the completion of fall arrest in near-falls and the completion of activity in ADL.**

Chapter 6.

Distinguishing the causes of falls in humans using an array of wearable tri-axial accelerometers

6.1. Abstract

Falls are the number one cause of injury in older adults. Lack of objective evidence on the cause and circumstances of falls is a barrier to effective prevention strategies. Previously studies established the feasibility of wearable miniature inertial sensors (accelerometer and gyroscopes) to automatically detect falls, to deliver medical assistance. In the current study, we extend this line of research, by developing and evaluating the accuracy of wearable sensors system for determining the cause of falls. Twelve young adults participated in experimental trials involving falls due to seven causes: slips, trips, fainting, and incorrect transfer of weight while sitting down, standing up from sitting, reaching and turning. Features (means and variances) of acceleration data acquired from four tri-axial accelerometers during the falling trials were input to a linear discriminant analysis technique. Data from an array of three sensors (left ankle + right ankle + sternum) provided at least 83% sensitivity and 89% specificity in classifying falls due to slips, trips, and incorrect weight transfer during sitting, reaching and turning. Classification of falls due to fainting and incorrect transfer during rising was less successful across all sensor combinations. Furthermore, similar classification accuracy was observed with data from wearable sensors as motion capture. These results establish the basis for development of sensor-based fall monitoring systems, providing information on the cause and circumstances for fall prevention.

6.2. Introduction

Falls are a major cause of injuries and deaths in older adults. Approximately 35% of community-dwelling older adults and 50% of older adults residing in long-term care facilities fall at least once per year [79, 178-180]. Over 90% of hip fractures and 60% of head injuries in this population are due to falls [79, 180, 181]. Clearly, the development of improved strategies to prevent falls and fall-related injuries in older adults is a major public health priority.

An important but poorly recognized barrier to fall prevention in this population is lack of objective evidence on how and why falls occur. Traditionally, our understanding of the mechanisms of falls in older adults has been based on interviews with the faller or witness, if any, which often occur weeks or months after the fall [86, 182]. However, falls are often un-witnessed [84-86], and recalling the details of falls is difficult even for young adults [183]. Combined with the frequent co-existence of multiple risk factors in individuals who present with a fall (e.g., impairments in musculoskeletal, cardiovascular, or cognitive function), this creates challenges in designing or selecting fall prevention strategies at the patient or population level.

Wearable sensors may address this barrier by providing objective data on the cause and circumstances of falls. Currently, the main application of wearable inertial sensors in the area of falls monitoring is to automatically detect falls, and alert care providers of such events to hasten the delivery of medical assistance [102, 110, 118, 150]. Collectively, these studies have shown convincing evidence that, at least in the laboratory environment, falls can be distinguished from daily activities with high accuracy (e.g. at least 95% sensitivity and specificity), based on the large accelerations applied to the head, torso or pelvis during impact, or the vertical and horizontal velocities of the body segments during descent [118, 150]. For example Wu [184] found that a threshold algorithm, based on peak values of vertical velocity from a 3D sensor on the waist, was 100% successful in separating falls from activities of daily living acquired in the laboratory with young participants.

In the current study, we focus our attention on the development of a complementary and clinically valuable application for wearable inertial sensors in fall

monitoring: determining the biomechanical cause of the fall. We recently showed that a machine learning algorithm based on linear discriminant analysis (LDA) was able to distinguish falls due to slips, trips and ‘‘other causes of imbalance’’ with 96% sensitivity, based on 3D kinematic data from a video-based motion capture system [152]. While such systems provide high acquisition rates and accurate 3D position data, they are costly and restricted to capturing movements within camera view. In the current study, we examined whether similar classification accuracy would be provided by off-the-shelf, wearable tri-axial accelerometers, with their local frames of references, gravity acceleration vector bias, and direct output of acceleration. We addressed this objective by conducting laboratory falling experiments with young adults who wore accelerometers placed at the sternum, waist and right and left ankles. We then examined how the location and number of sensors influenced the LDA routine accuracy in correctly classifying the causes of falls. When compared to our previous study, we expanded our analysis to consider, in addition to slips and trips, five distinct ‘‘other’’ causes of falls (fainting, and incorrect weight shifting while rising, sitting down, reaching and turning). For each case, we compared the classification accuracy of our LDA routine when utilizing data from video-based motion capture versus body-mounted accelerometers. Our results help to expand the basis for wearable sensors in fall prevention.

6.3. Materials and methods

6.3.1. Participants

Twelve young healthy participants (9 men and 3 women) ranging in age between 20 and 35 years, and of average height 171 cm (SD = 7) and body mass 71.8 kg (SD = 9.5), participated in the experiment. All participants were students at Simon Fraser University, recruited through advertisements posted on university notice boards. Each provided informed written consent, and the experiment protocol was approved by the Research Ethics Board at Simon Fraser University.

6.3.2. Experiment protocol

In the experimental trials, participants fell to the ground from standing height, simulating each of the seven underlying causes of imbalance (Figure 6.1). In all trials, participants fell onto a 30 cm thick gymnasium mattress, into which we inserted a 13 cm top layer of high density ethylene vinyl acetate foam so the composite structure was stiff enough to allow for stable standing and walking, but soft enough to reduce impact forces to a safe level. Prior to the start of the experiment, we conducted training sessions with each participant; for each type of fall, we displayed a representative video of a real-life fall in an older adult, and instructed the participant to fall in a similar fashion (Figure. 6.2).

The sequence of presentation of the various causes of falls was randomized, and each participant performed three trials for each cause. In slipping trials, participants walked over a low friction plastic sheet, and were made to slip backward by either rapidly translating the sheet (n = 3) or by simply instructing them to act out a backward slip (n = 3) without translation of the sheet. Tripping trials were simulated either by having a rope attached to the participant's right ankle become taut during the swing phase of walking (n = 3) or by instructing the participant to simply act out a trip over an obstacle (n = 3; a wooden block of approximately 10 cm width and 15 cm height), initiating a forward fall. In fainting trials, participants were instructed to stand on the gym mat and then suddenly relax (or collapse) the legs to act out a faint as naturally as possible (n = 3). In falls due to incorrect weight transfer while sitting down (IT-sitting) (Figure 6.2A), we instructed participants to begin in a standing position, and then lower the body in a controlled manner to simulate sitting down on a fictitious chair, and at the expected contact position, to lose their balance and fall backward (n = 3). In falls due to IT-rising (Figure. 6.2B), participants initially sat on a chair and were instructed to lose their balance while attempting to stand up (n = 3). In falls caused by IT-reaching (Figure 6.2C), participants were instructed to reach and pick up an object placed on the ground in front of them, primarily by bending at the waist and, after retrieving the object, to lose balance upon rising and fall backward (n = 3). Finally, in falls due to IT-turning (Figure 6.2D), participants were instructed to turn 180 degrees from standing, lose balance and fall (n = 3). No instruction was provided on the fall direction.

6.3.3. Data collection

During the trials, we used four tri-axial accelerometers (±10 g, Microstrain, Inc. G-Link) to acquire three-dimensional acceleration data at 128 Hz. The sensors were mounted bilaterally on the lateral malleoli, and at the anterior aspect of the waist and sternum, selected based on their feasibility for sensor placement on the human body. We also used an eight-camera motion analysis system (Eagle system, Motion Analysis Corp., Santa Rosa, CA) recording at 120 Hz to acquire the three-dimensional positions of reflective skin markers located at the four aforementioned anatomical locations. Position data were low pass filtered using a recursive, 4th order Butterworth filter having a cut-off frequency of 20 Hz and double differentiated to estimate accelerations.

6.3.4. Data analysis

Data analysis focused on determining whether the cause of falls could be accurately predicted from 3D acceleration data from accelerometers mounted bilaterally on the lateral malleoli, and at the front of the waist and sternum. In the single sensor category, we considered only the waist and sternum, and not the right or left foot sensors, considering that the asymmetry in foot movements associated with fall initiation would necessitate bilateral placement in any real life application of our sensor technology. Similarly, in arrays of 2–4 sensors, we only considered combinations of both right and left ankle sensors (i.e. never one alone). For each trial, we inspected acceleration data to determine the approximate time instant (T0) when the body first impacted the ground, registered as a sharp peak, which always exceeded 29.4 m/ s2 (3 g), in the resultant acceleration of the waist sensor [118, 150]. Acceleration data for the 1500 ms preceding T0 (Figure 6.3) were then input to our fall classification algorithm.

Our data classification routine treated each trial as a distinct data point. From our 12 participants, we collected and included in our analysis a total of 72 slips, 72 trips and 36 trials from each of the five other causes of falls. From each trial, we calculated the mean and variance in the X, Y and Z acceleration traces for each of the four sensors over the 1500 ms preceding pelvis impact. These outcomes resulted in a ‘‘feature vector’’ that ranged in dimension from six (for single sensor) to 24 (for four sensors). We used multi- class linear discriminant analysis (LDA) by developing seven linear

boundaries to classify the causes of falls. We split the feature vector into training and testing sets of equal size by choosing data from six participants for training and the remaining six for testing. The LDA procedure applies a set of projection operation to the feature space, which results in optimal separation between causes (fall types) [185, 186].

We applied our LDA routine to acceleration data from each sensor, and from each possible combination of 2, 3 and 4 sensors. In each case, we constructed confusion matrices and used these to calculate, for each cause of fall, the system's sensitivity (ability to detect actual events) as TP/(TP + FN)*100 and specificity (ability to distinguish non-events) as TN/(TN + FP)*100, where TP = true positive, FN = false negative, FP = false positive, and TN = true negative. For a given cause of fall (e.g., cause X), the total number of associated false positives was the number of trials where the actual cause was different than X, which were (incorrectly) classified by the algorithm as being due to cause X. In contrast, the total number of associated false negatives was the number of trials where the cause was actually due to X, which were not classified as X.

While recognizing that ''good accuracy'' is subjective, we ranked the performance of a given sensor location, or combination of sensors (ranging from one to four), based on the number of fall categories for which it provided over 80% sensitivity, selected on the notions that specificity was always higher than 80% (and in only one cause fell below 80%), and 80% sensitivity and 80% specificity represent a promising starting point for a clinically useful system.

In addition to predicting the causes of falls based on sensor acceleration data, we used the same LDA routine (and seven classification categories) to categorize falls based on acceleration data derived by double differentiating position data obtained from our video-based motion analysis system, and compared measures of sensitivity and specificity from the two data sources.

6.4. Results

The accuracy of our LDA algorithm in classifying the causes of falls depended on the location and number of sensors (Table 6.1). Overall, the best performance was provided by the three-sensor combination of left ankle + right ankle + sternum, which provided an average sensitivity of 78% and specificity of 97% over all causes of falls, and greater than 80% sensitivity (our criteria for ‘‘good accuracy’’) for five of the seven causes: slips (92% sensitivity), trips (97%), IT-reaching (89%) and IT-turning (94%) and IT-sitting (83%). The best scoring two-sensor combination was left ankle + right ankle, which provided an average sensitivity of 66% and specificity of 95% over all causes of falls, and good accuracy for slips (92% sensitivity), trips (97%) and IT-turning (83%). With a single sensor, the best performance was provided by a waist-mounted unit. This exhibited an average sensitivity of 69% and specificity of 95% over all causes of falls, and good accuracy for slips (92%) and IT-reaching (83%). The four-sensor combination of left ankle + right ankle + waist + sternum was less accurate overall than the three-sensor combination of left ankle + right ankle + sternum, with good accuracy in only three categories (slips, trips and IT-reaching).

The accuracy of our LDA algorithm also depended on the cause of the fall (Table 6.1). Slips, trips and IT-reaching were the easiest to distinguish. In each case, five of the seven sensor combinations provided more than 80% sensitivity. Fainting and IT-rising were the most challenging to distinguish. The best sensitivity for faints was provided by the waist + sternum (61%) while IT-rising was the waist alone or in combination with feet (78%).

Comparing performance of our LDA routine based on data from accelerometers versus video-based motion capture data (Table 6.2), showed that, for both methods, the best scoring combination was the same three-site combination of left foot + right foot + sternum, which provided good accuracy in five categories. The average sensitivity was slightly higher with accelerometers than motion capture (78% vs. 72%, respectively), and the average specificity for both methods was 96%.

6.5. Discussion

Falls in older adults are a major health problem, and lack of objective evidence on how and why these events occur is a major barrier to prevention. Wearable fall monitors may, in addition to detecting falls, provide objective information on the cause and circumstances of falls to direct fall prevention strategies. The current study contributes toward the design of such systems by providing evidence on the accuracy of an LDA classification routine in distinguishing seven distinct causes of falls, based on data from wearable accelerometer arrays collected in falling experiments with young adults.

As expected, we found that system accuracy varied with the nature of the sensor array. The best overall performance was provided by the three-sensor combination of left ankle + right ankle + sternum, which provided over 90% in classifying slips, trips and IT-turning, and over 80% sensitivity in classifying IT-sitting and IT-reaching, and thus met our criteria for ‘‘good accuracy’’ in identifying five of the seven causes of falls. Adding a fourth sensor at the waist did not improve classification accuracy, perhaps due to over-dimensionality in the feature space [187].

We also found that system accuracy depended on the cause of the fall. Both slips and IT-reaching (which involved backward falls with distinct torso rotations) could be accurately detected with a single sensor. In contrast, trips and IT-turning required sensors at the feet to distinguish the gait alterations leading to each of these types of falls. No sensor array provided good accuracy in distinguished fainting and IT-rising, with faints often misclassified as IT-turning, likely due to the fact that both categories tended to involve falling straight down.

Previously, we documented the accuracy of an LDA routine in distinguishing between three causes of falls (slips, trips, and ‘‘other causes’’) based on data from a video-based motion capture system [152]. In the current study, we compared results from wearable sensors and video capture, and found similar performance across the two techniques. In each case, the best results were provided by the three-site combination of ‘‘left ankle + right ankle + sternum,’’ which reinforces the notion that this array represents the strongest candidate for further development and evaluation. Moving forward, we feel

that wearable sensors, which continue to improve in miniaturization and battery life, offer a more viable solution than video capture (which suffers from limitations related to cost, occlusion of markers, and limited measurement volume) for long- term human movement monitoring. This study establishes a basis for that approach.

There are important limitations to this study. First, all falls were performed under controlled laboratory conditions by healthy individuals between the ages of 20 and 35, who fell on soft gymnasium mats. There are inevitable discrepancies between the falling patterns observed in our trials, and those of older adults who are the targets for our fall monitoring technology [133, 170]. However, a strength of our study was the selection of falls based on the causes and activities reported to be most common among older adults in long-term care [81], and the utilization in training sessions that incorporated video segments of typical real-life falls by older adults. Furthermore, in order to minimize the effect of surface stiffness on falling behavior, the top 13 cm layer of the mats consisted of high-density ethylene vinyl acetate foam. This provided the composite structure with a stiffness high enough to allow for stable standing and walking, but soft enough to reduce impact forces to a safe level. Second, our analysis focused on distinguishing the causes of falls, and not detecting the occurrence of a fall per se. Several recent laboratory studies provide convincing evidence that classification routines can detect an occurrence of a fall with high accuracy based on data from accelerometers located at waist or sternum (as included in our study) [110, 118, 150, 184], although additional field data from ‘‘real life’’ falls is required to verify and refine these approaches [133]. Our study establishes the ground- work for applications that provide information on the biomechanical cause of the fall, based on compatible sensor arrays. Finally, our analysis was restricted to the use of linear discriminant analysis to classify falls from acceleration data. Future studies should examine the potential improvements provided by alternative classification techniques, such as Support Vector Machines and decision trees. It remains possible, however, that specific causes of falls, such as faints, cannot easily be identified from only kinematics, and physiological data (blood pressure or muscle activity) are necessary complements to kinematic information for distinguishing such events.

In summary, we found that an array of up to three wearable 3D acceleration sensors (left ankle + right ankle + sternum), input to an LDA classification scheme, provided at least 83% sensitivity in classifying falls due to slips, trips, and incorrect transfer of weight during sitting, reaching and turning, but was less successful in classifying falls due to fainting and incorrect weight transfer during rising. Future work should examine whether system accuracy in distinguishing the cause of falls can be improved through alternative classification methods, or through different types of sensors (e.g., rate-gyros, altimeters, or blood pressure monitors), as precursors to clinical research examining how ‘‘cause of fall’’ monitoring systems affect treatment and prevention strategies, and future risk for falls, among high-risk older adults.

Table 6.1. Sensitivity and specificity of (class 7 LDA algorithm) 3D-sensor-arrays in distinguishing causes of falls from various sensor arrays.

Sensor combination (accelerometer data)	Slip (n = 36)		Trip (n = 36)		Fainting (n = 36)		IT-sitting (n = 36)		IT-rising (n = 36)		IT-reaching (n = 36)		IT-turning (n = 36)		Average (for specific sensor combo)	
	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %
One sensor																
Sternum	61	78	75	90	33	96	72	97	50	100	89	96	17	94	57	93
Waist	92	83	72	98	28	99	78	99	78	96	83	97	55	93	69	95
Two sensors																
L.ankle+R.ankle	92	98	97	99	33	97	33	96	67	99	61	90	83	89	66	95
Waist+Sternum	78	94	97	94	61	95	72	99	55	98	94	96	50	96	72	96
Three sensors																
L.ankle+R.ankle+waist	94	98	92	100	28	96	78	96	78	99	78	98	72	89	74	96
L.ankle+R.ankle+sternum	92	99	97	98	39	99	83	97	55	100	89	96	94	89	78	97
Four sensors																
L.ankle+R.ankle+waist+sternum	94	98	94	100	55	94	78	99	55	100	94	96	67	92	70	95
Average (over all sensor combos)	86	92	89	97	40	96	71	97	63	99	84	95	62	92	70	95

Notes: Sen = sensitivity; Spe = specificity

Table 6.2. Sensitivity and specificity of (class 7 LDA algorithm) 3D-marker-arrays in distinguishing causes of falls from various marker arrays.

Marker combination (accelerometer data)	Slip (n = 36)		Trip (n = 36)		Fainting (n = 36)		IT-sitting (n = 36)		IT-rising (n = 36)		IT-reaching (n = 36)		IT-turning (n = 36)		Average (for specific marker combo)	
	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %	Sen %	Spe %
One marker																
Sternum	100	90	42	97	39	99	33	97	94	95	91	92	72	90	63	94
Waist	89	89	69	98	05	98	11	99	55	99	50	87	83	84	52	93
Two markers																
L.ankle+R.ankle	89	99	80	99	33	99	28	96	78	100	33	89	100	80	63	94
Waist+Sternum	97	98	86	99	22	98	22	99	78	98	72	91	78	90	65	95
Three markers																
L.ankle+R.ankle+waist	89	99	86	100	28	99	33	96	89	100	91	88	100	85	69	95
L.ankle+R.ankle+sternum	92	98	83	99	33	99	28	97	89	99	83	89	100	89	72	96
Four markers																
L.ankle+R.ankle+waist+sternum	94	98	94	100	28	100	39	99	89	100	93	90	100	88	77	96
Average (over all marker combos)	93	96	77	99	27	99	28	97	82	99	65	89	90	86	66	95

Notes: Sen = sensitivity; Spe = specificity

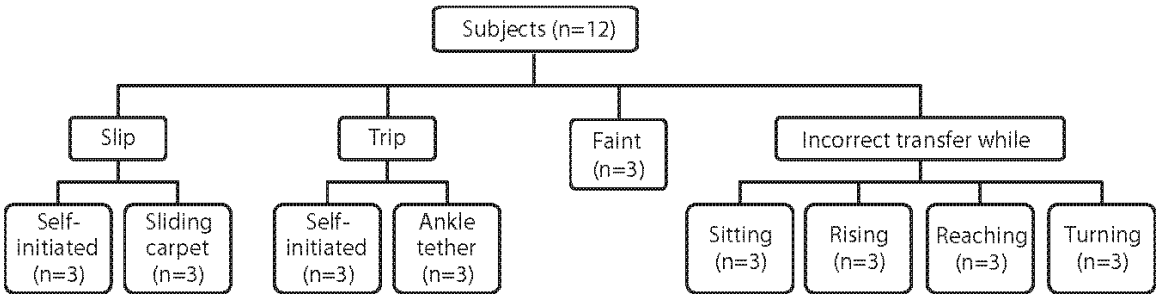

Figure 6.1. Flow chart indicating the various types of falls experienced by each participant.

Incorrect Transfer while sitting (IT-sitting)

real life IT-sitting

lab recreation of real life IT-sitting

A

Incorrect Transfer while rising (IT-rising)

real life IT-rising

lab recreation of real life IT-rising

B

Incorrect Transfer while reaching (IT-reaching)

real life IT-reaching

lab recreation of IT-reaching

C

Incorrect Transfer while turning (IT-turning)

real life IT-turning

lab recreation of IT-turning

D

Figure 6.2. **Laboratory simulation of falls in young adults due to incorrect weight transfer while (A) sitting, (B) rising, (C) reaching, and (D) turning. Video segments of real-life falls in older adults captured by digital video networks in long term care facilities (top panels [23]) were used to train young participants to mimic the falling behavior of older adults (bottom panels).**

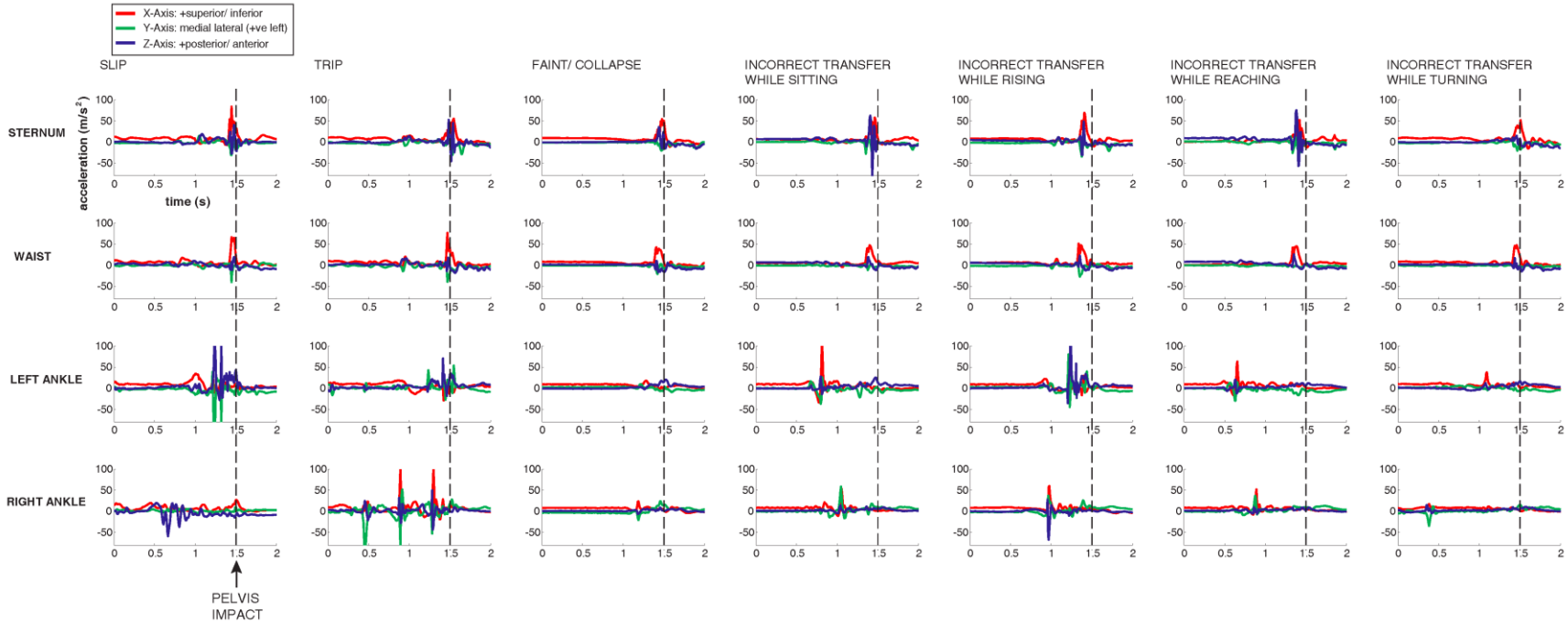

Figure 6.3. **Acceleration traces in the x, y, and z directions from a typical participant in falls due to incorrect transfer or shifting of body weight while (i) sitting, (ii) rising, (iii) reaching, and (iv) turning. Data from each fall are aligned so pelvis impact occurs at t = 1.5 s. Acceleration data for the 1.5 s preceding pelvis impact were input to our fall classification algorithm. The legends explain the coordinate reference frame for each fall. The vertical dashed line indicates the instant of impact. Note that the sternum and waist sensors typically record moderate accelerations until the instant of impact during the fall, when acceleration always exceeded 3 g (29.4 m/s2), allowing for accurate detection of the fall.**

Chapter 7.

Thesis synthesis and conclusion

My thesis research was motivated by the need to develop improved methods for automatic detection of fall-related events using wearable sensors. In particular, my work builds upon previous approaches to detect falls with wearable sensors, and extends the role of wearable sensors to pre-impact fall detection, near-fall detection, and cause of fall classification.

In my first study, I conducted laboratory experiments to compare the accuracy of traditional threshold-based fall detection algorithms to novel machine learning-based algorithms in distinguishing falls from ADLs. Several previous studies have examined the accuracy of wearable sensors systems to automatically detect falls, with the goal of alerting care providers and reducing the long-lie that often occurs after a fall. While system accuracies of up to 100% have been reported for detecting falls in laboratory experiments with young adults [81, 106, 107, 113], evidence suggests that the accuracy of these systems is considerably lower when tested with real-life falling data from older adults [133]. In an attempt to improve on existing approaches, I designed my laboratory experiments to more accurately simulate the characteristics (causes of imbalance and activities leading to falls) of real-life falls in older adults [81]. My experimental design was based on analysis of a library of 227 real-world falls in 130 older adults captured on video. Based on this video evidence, I selected the seven most common types of falls (combinations of causes of imbalance and activities at the time of falling). Young participants acted out each type of fall while wearing an array of sensors. I also included five types of near-falls and eight common activities of daily living (ADLs).

My results indicated that machine learning algorithms provided greater accuracy than threshold-based methods in distinguishing falls from non-falls, with SVM providing

the highest combination of sensitivity (96%) and specificity (96%), based on acceleration signals from single waist mounted sensor. In addition to highlighting the value of machine learning approaches for fall detection, this study describes improvements for researchers in the design of laboratory experiments that incorporate simulated falls, near falls, and ADLs.

In my second study, I tested the accuracy of my SVM fall detection algorithm in distinguishing falls from non-falls using real-world sensor datasets acquired with older adults, including 10 falls occurring over 392.5 hours of sensor data collection. My results indicate that the SVM classifier successfully detected 8 out of 10 real-world falls, and provided false positive rate from 0.05 to 0.15 false alarms per hour depending on the older adult dataset. This is the first study to test the accuracy of an SVM classifier on large datasets of real-world falls and non-falls, and demonstrate that it is comparable to the best results observed from threshold-based algorithms [133]. For sensor location on the body, while previous studies recommended attachment of the wearable fall monitor near the pelvis region, we found waist location for sensor placement inconvenient for older adults, as several older adults complained of discomfort during sitting and toileting, in which case the care staff had to remove the waist sensor. On the other hand, sensor attached at the sternum for fall monitoring was preferred by both older adults and care-staff. Furthermore, in this study, since three of the real-world falls captured using ±2g range accelerometers showed clipping effect, it is recommended that for fall recording the range of the accelerometers should be at least ±6g with at least 100Hz sampling rate to track the impact, while higher sampling rate (e.g., 200 Hz) and range (e.g., ±10 g) would be preferred.

My third study focused on the development of a system to detect falls during the descent phase (before impact) so that injures can be prevented through the deployment of protective equipment (e.g. inflatable hip or head protectors). In particular, I examined the effect of the data window size and lead-time on the accuracy of an SVM-based pre-impact fall detection system using signals from a single waist sensor. My results indicate that my system is able to detect fall events 187 ms prior to impact with at least 95% sensitivity and 90% specificity. While previous studies of pre-impact fall detection have reported lead times of approximately 300 ms using threshold-based techniques [103,

120, 188], my results are based on a more externally valid fall dataset, and further work is required to compare these techniques.

In study five, I conducted the first study to examine the ability of wearable sensor systems to identify near-falls (imbalance events followed by successful balance recovery), which are clinically relevant markers of fall risk in older adults. A system incorporating sensors at the feet and waist and a machine learning based classification scheme provided 100% sensitivity and 99% specificity in detecting near-falls.

My final study was also novel in examining whether information from wearable accelerometers could be used to accurately identify the cause of the fall. My Linear Discriminant Analysis (LDA) routine, using data from sensors at the ankles and sternum, provided 83% sensitivity and 89% specificity in classifying falls due to slips, trips, and incorrect shift of body weight during sitting, reaching and turning. My results establish a basis for the development of sensor-based fall monitoring systems that provide information on the cause and circumstances of falls, to direct fall prevention strategies at a patient or population level.

In closing, I highlight some important directions for future research in wearable fall monitoring technology. First, in my research, I was fortunate to be able to collaborate with the EU-based FARSEEING project [189] and access their unique library of sensor data of real-life falls in older adults to use in evaluating my fall detection algorithm. However, there is a need for larger datasets of this type for the development and testing of algorithms. Additional field studies with large numbers of older adults are required to gather sensor data during real-life falls, near falls and ADLs. Sharing of these data among researchers, as promoted by FARSEEING, should facilitate the rapid development of more accurate algorithms for detecting falls and fall-related outcomes. Second, there is a need for additional research on user acceptance issues with the technology, and the development of user interfaces that are effective for older adults and their care providers. Third, while my laboratory experiments included a similar number of fall and non-fall trials, in real life, the proportion of time spent falling is much less than the time spent performing daily activities. This discrepancy could have been responsible, in part, for the occurrence of false positives, and a more realistic distribution of ADL and

fall data should be used in training and evaluating classification models. Fourth, the features input to my machine learning classification models were means and variances in acceleration, and future work is required to determine whether improved accuracy may be achieved by models that consider additional features in the time domain (e.g., entropy, kurtosis, correlation between acceleration axes) and/ or frequency domain (e.g., Fourier transforms or discrete cosine transforms). Fifth, my results from Chapter 4 (Study 3) showed reliable pre-impact fall detection with 180ms lead-time. In this study, I obtained the fall detection accuracies for corresponding lead-times and window sizes by analyzing recorded sensor data using a desktop computer. Future studies should examine whether the on-device microcontroller can process sensor data in real-time, and perform classification using machine learning algorithm quickly enough to detect and response to falls (through airbags, etc.) in 180ms. Sixth, my results from Chapter 2 (Study 1) indicate that the most common source of false positives for machine learning algorithms is 'descending from standing to lying.' My results from Chapter 6 (Study 5) indicated that, for distinguishing the cause of the fall, the poorest classification accuracy was observed for fainting and incorrect weight transfer during rising. Future studies should explore whether classification accuracy can be improved through the integration of multiple models than run in parallel or sequentially. For example, separate classification models could be trained with signals from the pre-impact versus post-impact phases of the fall, and run sequentially. Alternatively, fusion algorithms that combine a machine learning algorithm (for the descent and impact phases of the fall) with a threshold-based algorithm (for post-impact analysis) may provide improved classification accuracy.

Finally, there are promising applications of wearable sensor technology for improving safe mobility in older adults, beyond automatic fall detection. Sensors are being integrated into standard clinical measures of fall risk (e.g., instrumented Timed Up-and-Go) [190], so that subjective scores from a therapist or a nurse can be complemented with patient-specific quantitative analysis. Another promising application for wearable sensors in rehabilitation is the ability to detect an individual's state of balance, and provide biofeedback (e.g., via vibration) as a form of sensory augmentation. Finally, wearable sensors have a promising role in real-time monitoring of the effects of interventions on mobility, balance, falls and near-falls.

As with fall detection, these applications must be highly reliable to realize the potential of wearable sensor technology in reducing health costs and improving the quality of life for older adults. With the current rate of hardware development, it is not difficult to envision wireless sensors the size of small plasters on the near horizon. However, software developers must keep apace, working closely with clinical researchers to develop systems that address the complexity of falls in older adults, and ultimately in evaluating the clinical effectiveness of these systems in modifying key outcomes such as falls, fall-related injuries, mobility, and fear of falling.

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