AN ANALYSIS OF THE ACCURACY OF WEARABLE SENSORS FOR DISTINGUISHING THE CAUSE OF FALLS

by

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ABSTRACT

Falls are the number one cause of injury in older adults. Wearable sensor arrays (e.g. accelerometers) represent a promising technique for determining the cause and circumstances of falls in high-risk individuals. Previous studies have shown that the occurrence of a fall can be sensed reliably from the high acceleration generated at impact. This thesis extends this research, by developing and evaluating a sensor array system for determining the cause of a fall. Sixteen young adults participated in trials involving falls due to slips, trips, and "other" causes. 3D acceleration data acquired during the falling trials were input to a linear discriminant analysis (LDA) technique. This routine achieved 96% sensitivity in detecting the cause of a fall using acceleration data from three markers (left foot, right foot and sternum). These results indicate the utility of a three node accelerometer array for distinguishing the cause of falls.

Keywords: Accelerometers; Falls; Injury; Linear Discriminant Analysis.

To my grandparents

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BACKGROUND AND OBJECTIVES

1.1 Falls in the elderly

Falls are the number one cause of injury in older adults. Approximately 35% of all adults over the age of 65 (Blake et al,. 1988; Prudham and Evans, 1981; Cambell et al., 1981) and up to 50% of older adults in long-term care institutions fall each year (Tinetti et al., 1987). Approximately 15-20% of falls result in a serious injury (Alexander et al., 1990). As discussed in the next section, hip fractures are the most common serious injury related to falls. However, head, wrist, shoulder and spine injuries are also a frequent serious consequence of falls among older adults. Furthermore, even when no injury occurs, falls can have deleterious physiological effects on the individual including "fear of falling", which can result not only in restricted activity but increased dependency on others and decreased social interaction (Howland et al., 1998; Howland et al., 1993).

1.1.1 Fall-related injuries

For Canadian seniors, falls are the most frequent cause of injury-related hospitalization, and account for 78 percent of injury-related deaths (Raina et al., 1997). This is a growing problem, as the number of falls and fall-related injuries will increase as the proportion of those aged 80 years and over in Canada is expected to double over the next 20 years (Statistics Canada, 1997).

Fall related injuries bring not only suffering to patients, but also represent a huge cost to society. In Canada, there were over 2 million injuries in 1995, accounting for more than $4.2 billion in direct health care cost. The most costly injuries were falls, totalling approximately $2.4 billion or 57% of total direct cost (Papadimitropoulos et al., 1997). Furthermore, over $980 million of the 2.4 billion in direct costs spent on falls was devoted to treating falls among the elderly. It is estimated that about 40% of falls leading to hospitalization are the result of hip fracture, and that the number of hip fractures in Canada will increase dramatically from 23,375 in 1993 to over 88,000 cases by the year 2041 as the Canadian population ages (The Hygeia Group, 1998).

1.1.2 Hip fracture

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 (Papadimitropoulos et al., 1997). Half of all older adults hospitalized for hip fracture cannot return home or live independently after the fracture (Scott, 1990). People older than 85 years are 10 to 15 times more likely to experience a hip fracture than are people aged 60 to 65 years. Also, the risk of sustaining a hip fractures is 10.5 times higher for women residing in long – term care (LTC) facilities than if they were living in the community, and less than 15 percent of LTC residents who sustain a hip fracture regain pre-injury ambulation status (Folman et al., 1994).

1.2 Cause and circumstances of falls in older adults

Given the high incidence and cost of fall injuries in older adults, it is important to understand and target the mechanisms that cause these events. Falls are complex events that can be defined as a sudden, unintentional change in position causing an individual to land at a lower level onto the ground or onto an object (Wolf et al., 1996). 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 centre of gravity beyond its base of support. Falls occur relatively commonly among persons of all ages (Talbot et al., 2005). However, most falls in young and middle-aged adults occur during sports or vigorous activities while falls in older adults often occur while performing daily activities such as walking, turning, reaching and transferring (Talbot et al., 2005). Slips and trips, along with "loss-of-balance", "leg gave away" or "don't know" are common self-reported causes for falls (Blake et al., 1988; Brocklehurst et al., 1978; Cumming and Klineberg 1994). Also, studies show that many fall events in older adults occur from the interaction between identifiable environmental hazards and increased susceptibility to hazards from the accumulated effects of age and disease. Postural control, body orientation reflexes, muscle strength and tone, and height of stepping all decline with aging, and impair the older individual's ability to avoid a fall after an unexpected event of loss of balance. Age-associated impairments of vision, hearing and memory loss also are responsible for an increase in the number of falls due to slips, trips and stumbles. In older adults, other specific causes of falls include disorder of the central nervous system, cognitive deficits, poor vision, drug side-effects, alcohol intake, anaemia, hypothyroidism, unstable joints, foot problems and acute illnesses. However, there are few objective measures of real-life falls in older adults, from which to directly assess the cause and circumstances of these events, and how they are affected by physiological and environmental variables.

1.2.1 Inaccuracy of self reported fall characteristics

Falls among older adults often go un-witnessed. Reports on falls in such circumstances are generated by directly asking questions to the older adult (Cumming et al., 1990), thus relying on the ability of the individual to remember and recall the fall event. Self-reporting and retrospective surveys are likely to misreport fall events due to inaccuracies in responses led by forgetting or denying falls, especially those not resulting in injury (Cummings et al., 1988). Such techniques may provide inaccurate estimates of the true incidence of falling (Peel. 2000). Furthermore, recent laboratory falling studies indicate that even young healthy adults have difficulty in accurately recalling the mechanics of falls, when interviewed immediately after the event (Feldman, 2009). In order to determine the true cause of falls among older adults, and develop and evaluate prevention strategies, improved techniques are required to measure and analyse movement strategies during real-life falls.

1.2.2 Fall mechanics

The way in which a person falls, or the "mechanics" of the fall, are known to influence the type of injury sustained. For example, slips are initiated just after heel strike, and involve forward sliding of the foot along the ground, resulting typically in backward fall. Indeed most falls due to slips result in a backward fall and backward falls onto the buttocks have much lower rates of fractures (Rubenstein, 2006). On the other hand, trips are caused by obstruction of forward movement of the foot during walking, usually due to the contact with an obstacle, and subsequent anterior rotation of the torso leading to a forward fall. Wrist fractures usually result from forward or backward falls onto an outstretched hand, while, hip fractures typically result from falls to the side.

1.3 Systems for monitoring mobility and detecting falls in older adults

1.3.1 Surveillance cameras

Recent work by Robinovitch et al., (2009) studies the types and circumstances of falls in older adults living in long term care facilities. In this study, fall videos captured through surveillance cameras were studied and analysed by a panel of experts. While providing valuable data, a drawback of this approach is the fixed number and locations of surveillance cameras and associated risk of falls going unrecorded. As an interesting side note, these investigators compared videos to incident reports filled by care attendants who witnessed the fall or asked the faller a set of questions regarding the fall. These incident reports were found to differ considerably from the video recording in describing the cause of the fall. This suggested inaccuracy may limit the effectiveness of fall prevention strategies based solely on incident reports.

1.3.2 Wearable sensors for detecting falls

Recently, the use of wearable instrumentation to record human movement, in areas such as gesture recognition and fall detection has gained much attention. This is due in part to the success in sensor miniaturization, low power consumption and performance. Inertial sensors have the potential to be used for assessing a wide range of human movements, including activities of daily living (ADL), balance and postural sway and falls in various environments. Table 1 describes previous studies using wearable sensors to distinguish fall event from activities of daily living. These studies have utilized accelerometers (Lindemann et al., 2005; Bourke et al., 2006; Chen et al., 2005; Quagliarella et al., 2008; Noury et al., 2003), gyroscopes (Bourke et al., 2008; Nyan et al., 2006), or a combination of both accelerometers and gyroscopes (Wu et al., 2008; Hwang et al., 2004; Noury et al., 2008). Ongoing barriers to the adoption of this technology in daily geriatric practices is limited by several factors, including inadequate ergonomics, concern among older adults of stigmatization of fragility and a lack of software (data analysis) algorithms to meaningfully interpret sensor data.

The ability to detect falls is especially valuable for alerting care personnel and delivering assistance to the faller. Thus, research on the development of wearable sensor systems to accurately detect falls is a rapidly growing area of investigation. Human falls are generally characterized by an impact on the floor followed by a near horizontal orientation of the legs or torso. Most wearable fall detectors are designed to detect one or both of these effects. Accelerometers are employed in the design to detect an impact, whereas tilt sensors or gyroscopes are used to determine the orientation of the faller after the impact and tilt transitions during descent. A variety of sensor locations have been employed, depending on the information desired and ease of mounting. Common locations for wearing fall detectors include the chest (Hwang et al., 2004), hips or waist (Wu et al., 2008), wrist or forearm (Degan et al., 2003), knee or thigh (Nyan et al., 2008) and head (Lindemann et al., 2005).

1.3.2.1 Post – impact fall detection

As described above, researchers have used different anatomical locations to mount sensors and have employed different techniques to detect falls. Such efforts can be divided into two main categories based upon whether the detection occurs prior to or after impact of the body with the ground (Table 1). The most common and simple methodology for fall detection is by using a tri-axial accelerometer with simple threshold-based algorithms on acceleration magnitude to detect impact. Such algorithms can be used to automatically alert a nearby call centre of a fall event when the threshold value of acceleration is exceeded.

Bourke et al., (2007) introduced a threshold algorithm to distinguish between normal activities and falls. A set of prescribed daily activities were performed by 10 community dwelling older adults (3 women, 7 men) which included sitting down and standing up from chairs of various heights, getting in and out of a car seat, lying down and standing up from a bed and walking normally for 10 meters. Ten young adults simulated falls in forward, backward and lateral directions. Subjects were instructed to fall freely without breaking the falls. The ability to discriminate falls from normal activities was examined using two tri-axial accelerometers mounted on the thigh and sternum. The authors constructed a threshold algorithm based on investigation of peaks in accelerations from the thigh and sternum. Under the test conditions, this system proved 100% successful in fall detection after the body impact with the ground.

1.3.2.2 Pre – impact fall detection

Unlike post – impact fall detection systems, those that employ early detection of falls before the body impacts the ground offer the potential to prevent fractures (for example through an "inflatable" hip protector). During a fall, there is typically a period of “free fall” during which the vertical speed of the body segments increases with time due to gravitational acceleration. Based on this notion, Wu, (2000) compared features of the velocity profile of the trunk that separated daily activities from fall events, with the goal of developing a technique for automatic detection of falls during the descending phase prior to impact. Normal activities included walking, rising from a chair and sitting down, descending stairs, picking up an object from the floor, transferring in and out of a tub and lying down to a bed. In addition to normal activities, three young healthy adults recruited for the experiment performed falls in the forward and backward direction. The authors reported that all normal activities (n = 116) were identified whereas from 46 fall trials, 45 were identified accurately. Also, the system identified the falls with an average lead-time of 420 milliseconds prior to the pelvis impacting the ground. Brief descriptions of additional studies that address pre and post fall detection are listed in Table 1.

1.4 Goals and objective

To date, we have a lack of understanding of the cause or precipitating circumstances for falls in older adults, and how these are associated with intrinsic (dizziness, weakness etc.) and extrinsic factors (environmental hazards causing slipping, tripping etc.). Improved technology in this area should allow us to develop more specific and alternative measures for the prevention of falls in the elderly population.

The main aim of this thesis is therefore to develop a wearable sensor system that can accurately determine the cause of a fall, between categories such as slip, trip, faint, or incorrect transfer while sitting, standing, reaching, or turning. I address this goal by examining how the location and number of acceleration sensors influence the accuracy of a data analysis classification scheme in distinguishing the above-mentioned types of falls. In particular, I used a motion capture analysis system to acquire kinematic measures of falls with young adults in a laboratory setting. My experiments simulated three general types of fall causation: a) slips, b) trips and c) others causes. “Other causes” included five sub-categories: i) fainting, ii) incorrect transfer while sitting on a chair, iii) incorrect transfer while standing up from a chair, iv) reaching and v) turning. I then developed a linear discriminant analysis technique using Fisher's criterion to classify fall types as based on acceleration from various body-mounted sensors, and finally examined how system's accuracy depends on sensor number and location.

In summary, my thesis research addressed the following objectives;

a) To design an experiment protocol to simulate various common causes of falls among older adults;

b) To conduct laboratory experiments using this protocol with young adults to acquire body segment motions during these falls;

c) To develop a scheme to analyse experimental acceleration data based on Linear Discriminant Analysis to classify falls into the various categories (slip, trip or other causes); and

d) To conduct analysis to examine how the location and number of sensors influences the system's accuracy in distinguishing the causes of falls.

1.5 Tables

Table 1-1: An overview of fall detection research studies.

STUDY	SENSOR ARRAY		TESTING CONDITIONS		SYSTEM ACCURACY	TIME OF FALL
	Type of sensor(s)	**Location of sensors**	**Nature of falls (types and subjects)**	**Activities of daily living (types and subjects**	**%**	**Relative to Impact (ms)**
Wu, (2000).	Reflective Markers (Motion Capture System)	C3 T2 L5	3 Young Adults Tripping, Backward falls, Forward falls	3 Young Adults Walking, rising from a chair and sitting down, Descending stairs, Picking up an object from the floor, Transferring in and out of a tub, Lying down to a bed	Out of 116 ADLs and 46 falls Sensitivity = 98% Specificity = 100%	Falls detected 420 msec before end of fall.
Wu and Xeu, (2008).	Accelerometer and Gyroscope.	Waist	10 Young Adults Forward fall, Backward fall, Sideways fall, Down fall	14 older Adults Walking normally and sway walking, Sitting down and rising, Picking up an object from the floor, Transferring in and out of a tub, Lying down and getting up from a bed, Tripping, Being pushed, Drive a car, Use escalator	Sensitivity = 100 Specificity = 100	Falls were detected in 70 – 375 msec prior to impact.
Tamura, et al., (2000).	Photo sensor	Left lumbar region	1 Young Adult Dummy falls	1 Young Adult and 14 Hemiplegic patients during their rehabilitation training, Walking straight Ascending and descending stairs	False alarm occurred during: Person changed clothes, Rode bicycle, Went to bed	Falls were identified after the body impact
Hwang, et al., (2004).	Accelerometer, Gyroscope and tilt sensor	Sternum	3 Young Adults Forward fall, Backward fall, Sideways fall	3 Young Adult Sitting and standing, Normal daily activities	Out of 30 falls 4 were not identified. Total system accuracy was 96.7%	Falls were identified after the body impact.
Lindemann, et al., (2005).	Accelerometer	Head	1 Young Adult Forward fall, Backward fall, Sideways fall, Collapse, Fall while picking an object from floor	1 Young Adult Sitting on a chair, Lying down, Walking, Running, Stair climbing	False alarm triggered when the device was hit by the hand.	Falls were identified after the body impact.
Bourke, et al., (2008).	Gyroscope	Sternum	10 Young Adults Forward fall, Backward fall, Sideways fall	10 Older Adults Walking, Sitting and standing up from a chair, Getting in and out of a car seat, Lying down and standing up from a	Falls and ADLs were detected accurately. Sensitivity = 100%	Falls were identified after the body impact.

				bed	Specificity = 100%	
Bourke, et al., (2006).	Accelerometer	Sternum and thigh.	10 Young Adults Forward fall, , Backward fall, Sideways fall	10 Older Adults Walking, Sitting and standing up from a chair, Getting in and out of a car seat, Lying down and standing up from a bed	Separate threshold values were defined for thigh and sternum. Sensitivity = 100% Specificity = 100%	Falls were identified after the body impact.
Srinivasan, et al., (2007).	Accelerometer and a motion detector	Accelerome ter on waist, motion detector on wall	15 Young Adults Forward fall, Backward fall, Sideways fall	15 Young Adults Sitting, Standing, Walking, Walking fast, Hopping, Climbing up, Climbing down, Climbing down, Rotating in a chair	There was no false alarm and out of 96 falls 91 were detected accurately.	Falls were identified after the body impact.
Chen, et al., (2005).	Accelerometer	Waist	2 Young Adults Forward,Backward and sideways fall	2 Young Adults Walking, Sitting	Sensitivity = 100% Specificity = 100%	Falls were identified after the body impact.
Nyan, et al., (2008).	Two accelerometers and a gyroscope	Thigh and waist	21 Young Adults Fainting	21 Young Adults Walking, Sitting down and standing up from a chair, Lying, Ascending and descending stairs	Out of 216 ADLs and 42 falls system showed: Sensitivity = 94.5% Specificity = 100%	Falls were detected (prior to impact) with an average lead time of 700 msec.
Quagliarella, et al., (2008).	Accelerometer	Not mentioned	10 Young Adults Forward fall, Backward fall, Sideways fall	10 Older Adults i. Walking forward, Walking and going down one step, Walking and then sitting on a chair, Walking then sitting down and finally lying down on a bed, Walking and then picking up an object from the floor	Out of 200 ADLs and 200 falls system showed: Sensitivity = 100% Specificity = 100%	Falls were detected after the impact.
Noury, et al., (2003).	Accelerometer	Under the left armpit	10 Young Adults Backward fall ending in sitting, lying and lateral lying, Forward fall ending in alying and with rotating motion, Syncope ending with sitting, lying and lateral lying	10 Young Adults Normal walking then bending down and kneeling, Normal walking and then hitting the wall laterally, Sitting down and then lying on bed, Standing up and then sitting on a chair.	Out of 200 ADLs and 550 falls system showed: Sensitivity = 79% Specificity = 83%	Not mentioned

2: CHAPTER 2
AN ANALYSIS OF THE ACCURACY OF WEARABLE SENSORS FOR DETECTING FALLS CAUSED BY SLIPS AND TRIPS

2.1 Introduction

Wearable kinematic sensors, typically consisting of accelerometers and/or gyroscopes, represent a promising technique for determining how and why falls occur in older adults. This information is essential for the development of improved strategies for reducing the risk for falls and fall-related injuries (Tinetti et al., 1997; Nevitt and Cummings, 1993; Schwartz et al., 1998), and for understanding how physiological and environmental variables contribute to falls. Currently, our understanding of the cause and circumstances of falls occur is based on self-reports of fall events, which may be unreliable (Nevitt and Cummings, 1993; Cummings et al., 1988), or witness accounts, which are often unavailable (Hayes et al., 1993; Nurmi et al., 1996; Wagner et al., 2005).

Wearable sensors represent a promising technique for providing objective information on the fall mechanism. However, to date, fall-related research on wearable sensor systems has been restricted to a single outcome - detecting the occurrence of a fall (Lindemann et al., 2005; Bourke et al., 2006; Chen et al., 2005; Quagliarella et al., 2008; Noury et al., 2003;Bourke et al., 2008; Nyan et al., 2006; Wu et al., 2008; Hwang et al., 2004; Noury et al., 2008). An important application of such data is the automatic alerting of caregivers that a fall has occurred. However, the potential utility of wearable sensor systems extends beyond detecting a fall, to applications such as prompting balance recovery responses, triggering the deployment of protective clothing (such as inflatable hip and head protectors (Fukaya and Uchida, 2008)), or providing information on fall severity and related injuries. Furthermore, wearable sensor systems have the capacity to provide insight on the cause and activity at the time of a fall. However, a major challenge to engineers in designing these systems is to establish the sensor hardware, and related data analysis routines, necessary to provide accurate information on the outcome of interest.

In this study, my goal was to develop a wearable sensor system, and a related data classification scheme, for accurately characterizing the cause of falls due to slips, trips and other types of loss-of-balance. I addressed this goal by conducting laboratory "falling experiments" with young adults, acquiring whole-body kinematic data for a wide range of fall causes. I then systematically input acceleration data, from the time interval immediately preceding the fall, into a linear discriminant analysis classification routine, to determine how system accuracy in predicting the cause of fall depended on the number and location of the accelerometer sensors. My results indicate that high system accuracy for detecting the cause of fall can be achieved with as few as three sensors. My methods serve as a template for the development of additional applications of wearable sensors systems in falls research and prevention.

2.2 Material and methods

2.2.1 Participants

Sixteen young healthy individuals (12 men and 4 women) participated in this study with ages ranging from 20 to 35 years (mean = 25.6 yrs, SD = 3.8). All participants were either "under graduate" or "graduate" students at Simon Fraser University and were 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.

2.2.2 Experimental Protocol

The experiment protocol for my laboratory falling experiment was based on recent efforts by our laboratory to examine the causes of real-life falls in older adults residing in long-term care, as captured on video by a large network of digital video cameras (Robinovitch et al., 2009). Based on these observations, I simulated these specific classes of fall causation: slips, trips, and "other" causes (Figure 2-1). Prior to the start of the experiment, each subject was shown specific videos (Figure 2-2) from our records of falls in older adults due to slips, trips, and five other causes (fainting or syncope, reaching for an object, turning, incorrect weight shifting while sitting down on a chair and while rising from sitting). Subjects were instructed to imitate these falls as accurately as possible during the experimental trials, as described below.

In slipping trials, subjects were instructed to walk over a low friction plastic sheet, and either acted out a slip (n = 6), or were made to slip by rapidly translating the plastic sheet (n = 6) under their feet (Figure 2-2). I acquired 12 trials in each condition, in half of which, I instructed the subject to try to recover balance, and in the other six I instructed him/her to fall. Tripping trials were simulated either by having a rope tether attached to the subject's ankle to suddenly become taut or by instructing the subject to act out tripping over an obstacle (a wooden block of approximately 10 cm width and 15 cm height). The length of the tether rope was adjusted to become taut during the middle of the swing phase of the third step. Again, 12 trials were acquired, half of which involved balance recovery, and the other half falls. In "other fall" trials, the subject was instructed to act out falls due to five different causes (n = 3 per cause): fainting (or syncope), reaching for an object, turning, incorrect weight shifting while sitting down on a chair and while rising from sitting. I also acquired trials with each participant involving normal walking (n = 3).

In the current analysis, I only considered trials that resulted in a fall. Therefore, over the 16 subjects, a total of 96 slips, 96 trips and 288 "other cause" trials were analyzed.

2.2.3 Data collection

During each trial, I used an eight camera motion analysis system (Eagle system, Motion Analysis Corp.) recording at 120Hz to acquire the three-dimensional positions of 22 reflective skin markers. The markers were located bilaterally on the lateral malleolus, lateral epicondyle of the femur, greater trochanter, anterior superior iliac spine, acromion, lateral epicondyle of the humerus, dorsal surface of the hand, scapula and at the sternum, C7 vertebrae, sacrum and the front, top and back of the head.

Position data were low pass filtered using a recursive Butterworth filter (4th order, cut-off frequency 20 Hz) and double differentiated to estimate accelerations.

2.3 Data Analysis

Data analysis focused on determining whether the cause of falls could be accurately predicted from 3D acceleration data from five key anatomical locations (left foot, right foot, waist, sternum and head), selected based on their feasibility for sensor placement on the human body. For each trial, I inspected motion data to determine the approximate instant (T_0) when the pelvis first impacted the ground. Acceleration data for the 1500 milliseconds preceding pelvis impact were input to my fall classification algorithm (as described below). Previous studies (Hsiao and Robinovitch, 1998 and, Feldman and Robinovitch, 2007) have shown that the time interval between the loss of balance and the fall impact range from 450 milliseconds to 750 milliseconds with a mean value of about 700 milliseconds. Thus, I regarded acceleration trajectories over a time window of 1500 milliseconds prior to the pelvis impact as sufficient to capture the initiation and descent phase of each fall, and this was indeed shown to be the case for all falls analysed (Figure 2-3).

From each of the five markers' X, Y and Z acceleration traces, I calculated the mean and variance over the 1500 ms preceding pelvis impact. These outcomes resulted in a 30 dimensional "feature vector". Based on the assumption that the feature vectors from the three fall types were linearly separable, I used Linear Discriminant Analysis (LDA) using Fisher's criterion to classify the causes of falls. In the procedure I split the feature vector into training and testing sets of equal size by choosing data from the first eight subjects for training and the following eight for testing. The procedure transforms a classification problem from a higher to lower dimensional feature space through a set of projection operations, which results in optimal separability among different classes (Baudat and Anouar, 2000; Muller et al., 2001). Classifying two or more sets of data, can be achieved by maximizing the ratio of between-class scatter as divided by within-class scatter:

$$\mathrm{J}(\mathrm{w}) = \arg max_{\mathrm{w}} \left(\frac{\mathrm{w}^{\mathrm{T}} \mathrm{S}_{\mathrm{b}} \mathrm{w}}{\mathrm{w}^{\mathrm{T}} \mathrm{S}_{\mathrm{w}} \mathrm{w}} \right)$$

where "w" is a linear transform, "S_b" is the between class variance, "S_w" is the within class variance, and "$argmax_w$" refers to maximizing the above equation. The generalization of the within-class "S_w" and the between-class scatter "S_b" for "K" classes are given by the following expression:

$$m_k = \frac{1}{|N_k|} \sum_{n \in C_k} x_n ,$$

$$\mu = \frac{1}{N} \sum_{k=1}^{K} N_k \, \mu_k \quad ,$$

$$S_w = \sum_{k=1}^{K} \sum_{n \in C_k} (x - m_k)(x - m_k)^T \ ,$$

and

$$S_b = \sum_{k=1}^{K} N_k (m_k - \mu)\,(m_k - \mu)^T.$$

Here m_k is the sample mean for the k^{th} class, N_k is the number of patterns in class C_k, $|N_k|$ indicates the number of vectors in the k^{th} class and $N = \sum_k N_k$ in the total number of data points (Bishop, 2006).

I conducted linear discriminant analysis using acceleration data from each marker, and for each possible combination of 2, 3, 4 and 5 markers. In each case, I then constructed confusion matrices (Tables 2-1 to 2-15) and used these to calculate sensitivity, specificity, precision and accuracy (Figure 2-4 B) as follows:

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \times 100\ ,$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \times 100\ ,$$

$$Precision = \frac{True\ Positive}{True\ Positive + Flase\ Positive} \times 100\ ,$$

and

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \times 100.$$

where true positive, false positive, true negative and false negative are explained graphically in Figure 2-5 and defined specifically for each fall cause in Figure 2-4 B. However, results will primarily focus on system's sensitivity and marker location or combination of markers will be ranked based upon the Highest Minimum Sensitivity across the three conditions.

2.4 Results

The accuracy of the linear discriminant classification algorithm in classifying the cause of falls depended strongly on the location and number of markers, and varied considerably between the different types of falls (Table 2-16). With a single marker, the best sensitivity was achieved by the "head" and "waist" markers, which provided at least 52% sensitivity. In contrast the sternum marker provided only a minimum of 31% sensitivity. The single markers, head, sternum and waist, were most effective at classifying other causes of falls with sensitivities 85%, 92% and 96% respectively, and least effective at classifying trips (52%, 31% and 52% respectively). With a single waist marker, system was able to detect both slips and other causes of falls with 96% sensitivities whereas, head and sternum markers showed 79% sensitivities in identifying slips. With the single markers results showed that both slips and other causes could be detected with at least 79% sensitivities but trips were more difficult to classify with a single marker (52% sensitivity for waist or head marker).

With two markers the best sensitivity was observed with the combination of left foot + right foot, which provided at least 79% sensitivity. In comparison, markers combinations of waist + sternum, and waist + head, provided at least 54% and 56% sensitivities respectively. The combination of left foot + right foot provided accurate detection of trips and other falls with 92% and 90% sensitivities respectively, but was less successful in classifying slips (79% sensitivity). On the other hand, the waist + sternum combination, and the waist +

head combination, were accurate in determining slips (with 100% and 96% sensitivities, respectively) and other causes (with 98% and 97% sensitivities) but less accurate for trips (with 54% and 56% sensitivities). Similarly, the sternum + head combination was effective for detecting slips (89%) and other causes (92%), but not for trips (71%).

The best sensitivity was observed with three markers, left foot + right foot + sternum, which provided at least 96% sensitivity in all three fall types. The second, and the third best three-marker combinations were left foot + right foot + waist and, left foot + right foot + head, with at least 89% and 87% sensitivities respectively. Also, results showed that even though upper extremity markers (waist, sternum and head) provided high sensitivities in identifying falls due to slips and other causes, the markers at feet were found critical to accurately classify falls due to trips. This observation was also supported by three markers combination of waist + sternum + head, which successfully detected slips and other causes with 94% and 97% sensitivities respectively but provided only 58% sensitivity for trips.

The minimum sensitivity was no better with four and five markers than with three. With four markers, the best sensitivity was observed with the combination of left foot + right foot + waist + sternum, which provided at least 94% sensitivity. The other two four-marker combinations each provided at least 89% sensitivity. Moreover, with four and five markers combinations, system did not show a noticeable difference between sensitivities in detecting slips and other causes (reference: Table 2-16).

In addition to sensitivity, other measures such as specificity, precision and accuracy were also taken into account in evaluating the performance of the wearable sensor system. Specificity (risks for fall positives) was generally high throughout the results. However, it was found decreasing below 80% in only one case when a single sternum marker was used in classifying falls due to "other causes". Precision (proportion of true positives against all positive results) was found to be lower for slips than for trips and "other causes". The three-marker combination of left foot + right foot + sternum provided the highest precision (of 94%, 87% and 100% in evaluating falls due to slips, trips and "other causes" respectively). Accuracy (proportion of true results in the population) was also found high with the three-marker combination of left foot + right foot + sternum providing al least 87% accuracy.

2.5 Discussion

This study examined the utility of a wearable sensor array for detecting the causes of falls acquired in a laboratory setting. My results indicate that three dimensional acceleration data from three markers (mounted at left foot, right foot and sternum) entered into a linear discriminant model provide at least 96% sensitivity in distinguishing falls due to slips, trips and other causes. In contrast, the best two marker combinations (left foot + right foot) provided a minimum sensitivity of only 79%. This work contributes to the development of comprehensive fall monitoring systems based on wearable sensors, which might also provide information on characteristics such as the activity at the time of the fall, impact severity, ability to rise after falling and physiological variables (EMG, ECG) that may provide further insight on the cause of falls.

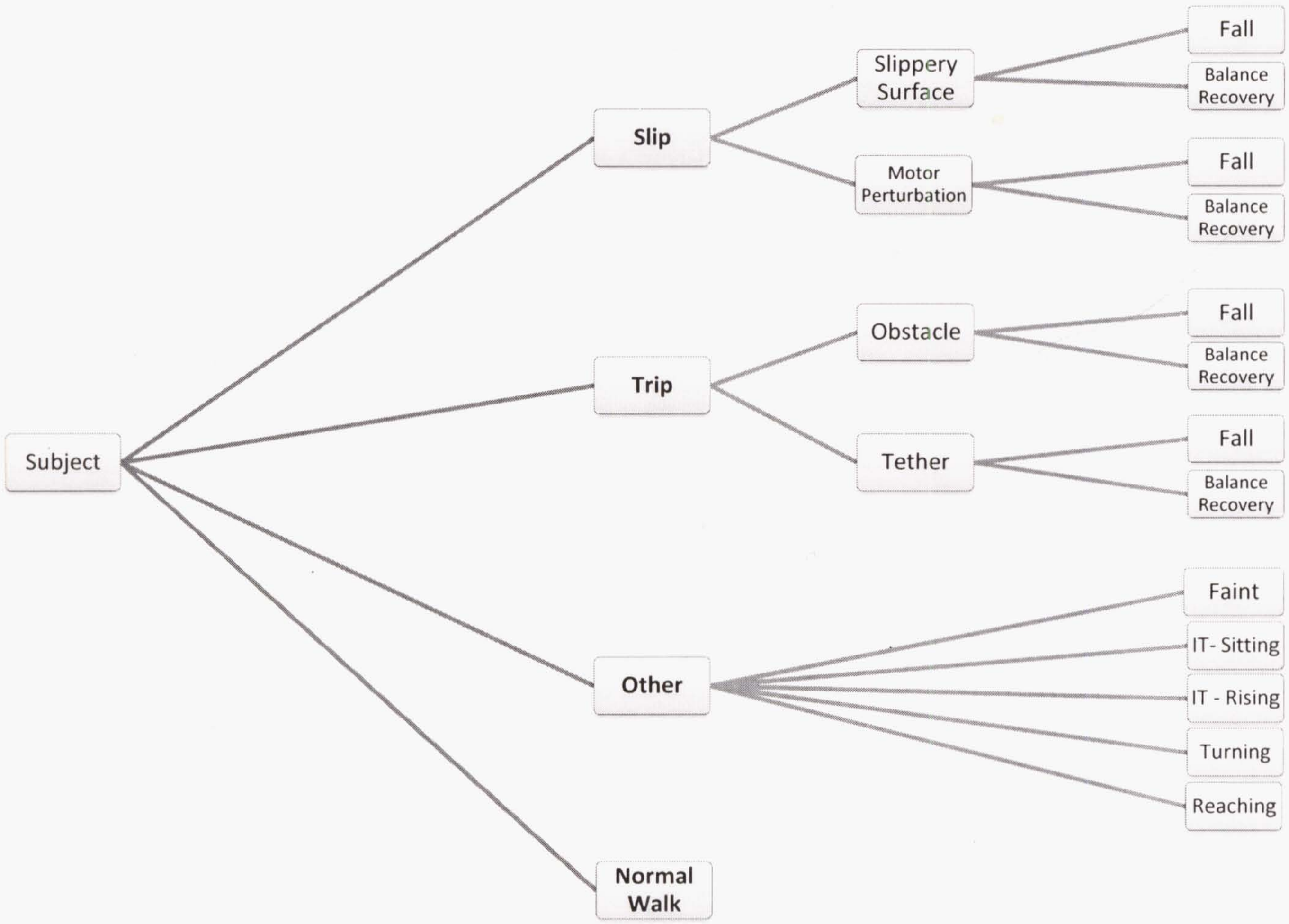
The need for sensors at three anatomic sites (left foot + right foot + sternum) reflected the observation that no two-sensor combination was able to capture body kinematics unique to each fall type, and achieve high accuracy in classifying all three types of falls. Slips are initiated just after heel strike, and involve forward sliding of the foot along the ground, resulting typically in backward fall. I found that such falls could be accurately detected with a single marker at the waist (96% sensitivity) and with combinations of waist + sternum or waist + head. On the other hand, trips are caused by obstruction of forward movement of the foot during walking, usually due to contact with an obstacle, and subsequent anterior rotation of the torso leading to a forward fall. A single marker had poor sensitivity (52%) for detecting such falls, which require sensors on both right and left foot. In contrast, any of the two marker combinations I examined was accurate in distinguishing falls due to “other causes” from those due to slips and trips. Collectively, these observations for two-marker combinations explains why three markers are required for comprehensive “cause of fall” detection.

Table 2-16 also illustrates specificity, precision and accuracy as measures of system performance. Specificity was often higher than sensitivity, which suggests that the system was better at classifying “negatives” than “positives” (Figure 2-6). However, one exception was noted for the sternum marker, which often misclassified falls due to slips and/or trips as due to “other causes”. In general, precision was lower than sensitivity, suggesting a higher number of false positives than false negatives. In terms of accuracy, the three-marker combination of left foot + right foot + sternum provided 98%, 96% and 97% accuracy in classifying falls due to slips, trips and “other causes” respectively.

There are important limitations to this study. Due to safety concerns, all falls were performed by healthy individuals between the ages 20 and 35 years. There are inevitable discrepancies between the falls of these young individuals and older adults. Also, all falls were performed under controlled laboratory conditions. Furthermore, acceleration data analysed to classify three fall causes, were calculated by double differentiating position data obtained from the Motion Analysis System. It can be argued that the proposed wearable sensors (accelerometers) may have different X, Y and Z - axis acceleration profiles (due to the non-static frame of reference as opposed to camera based Motion Capture System). However, the strength of my study is the application of a Machine Learning algorithm (Linear Discriminant Analysis) that allows the system to change behaviour based on available data. Therefore, it is expected that my system would behave in a similar manner with accelerometer data as was observed in this study. Another strength of my study is the utilization of video segments of real life falls by older adults in our training session. During the course of this experiment, I also included two types of slips and trips (self induced and perturbation based), and five types of "other falls" to enhance external validity.

In conclusion, I developed a cause of fall detection strategy based on wearable sensors, and found this provided 96% sensitivity in distinguishing slips, trips and other causes of falls based on 3D acceleration data from the right foot, left and sternum input to a linear discriminant model. Placing sensors at different body locations (such as head and sternum) presents an issue in itself when considering the size of sensor units found in market today. However, one may expect that, within a years' time, sensors may become available the size of "band-aids", which would enhance both compliance and sensor placement. Furthermore, the potential utility of the proposed wearable sensor system extends beyond detecting the causes of fall, to applications such as prompting balance recovery responses, triggering the deployment of protective clothing (such as inflatable hip and head protectors), or providing information on fall and injury severity. The method employed here provide a useful templte for the development and evaluation of such efforts.

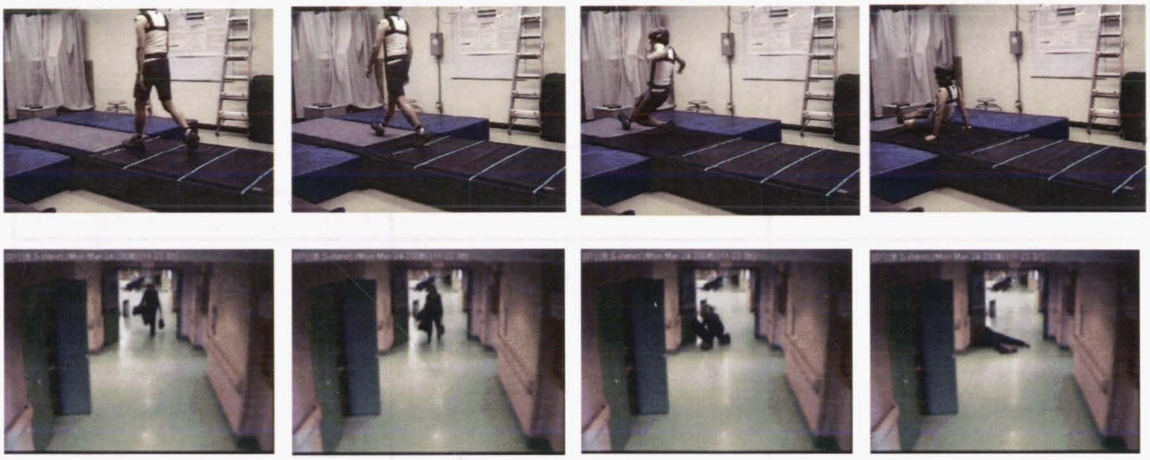
2.6 Figures



Subject
Slip
Trip
Other
Normal Walk
Slippery Surface
Motor Perturbation
Obstacle
Tether
Fall
Balance Recovery
Fall
Balance Recovery
Fall
Balance Recovery
Fall
Balance Recovery
Faint
IT- Sitting
IT - Rising
Turning
Reaching

Figure 2-1: Flow chart representing experiment protocol.The extended branches show the various types of falls that subjects were instructed to imitate. Sixteen subjects (12 males and 4 females) performed each trial three times, resulting in 96 falls due to slips, 96 due to trips and 288 due to “other causes”

A Slip and fall



B Trip and fall

Figure 2-2: Simulation of falls due to slips and trips in laboratory. The figues show comparison between real-life falls captured on surveillance cameras in long term care (LTC) facility and fall simulated through young adults in laboratory. (A) Comparison between a simulated slip and real-life slip. (B) Comparison between a simulated trip and real-life trip.

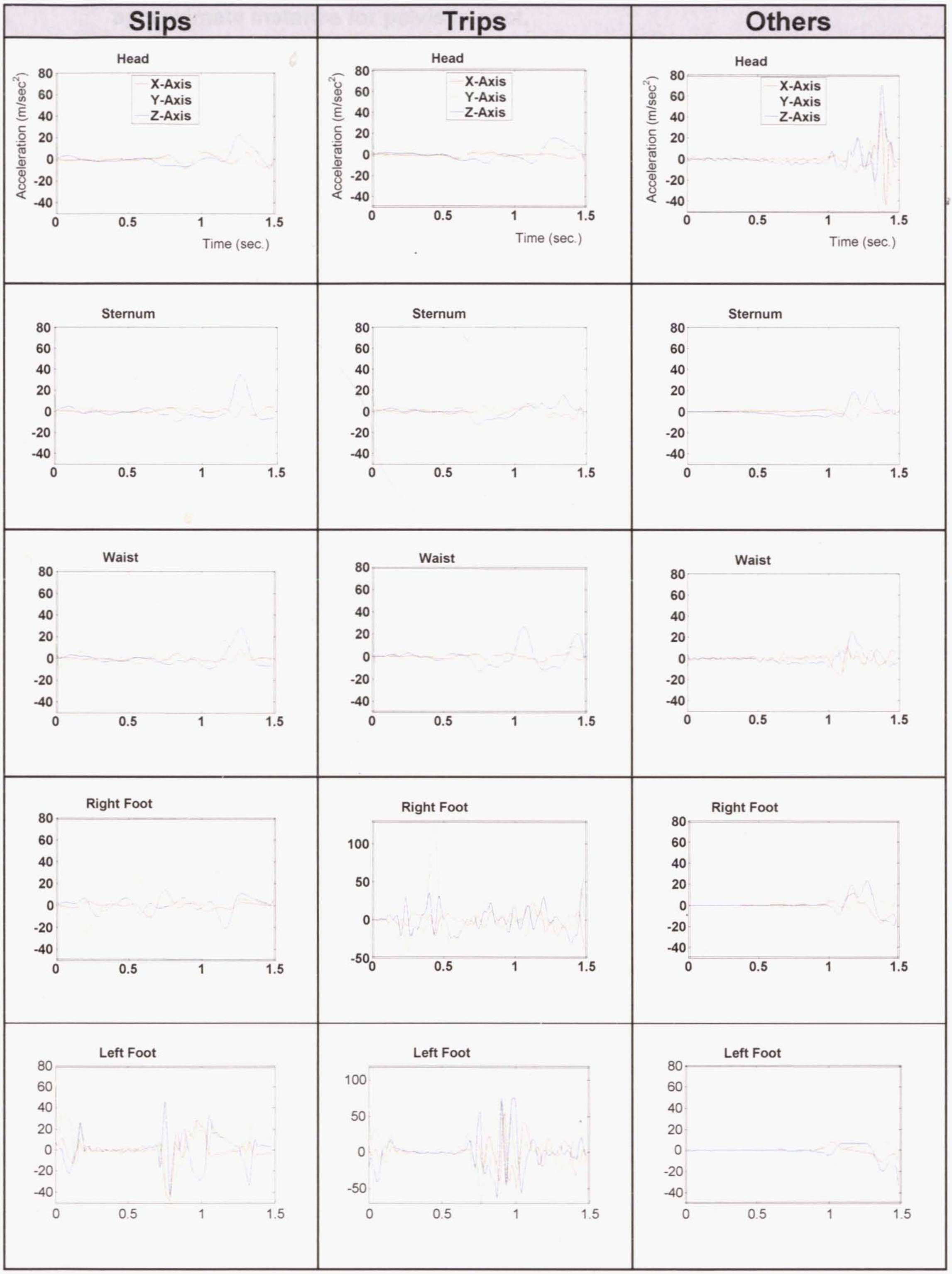

Slips
Trips
Others
Head
X-Axis
Y-Axis
Z-Axis
Acceleration (m/sec²)
Time (sec.)
Sternum
Waist
Right Foot
Left Foot

Figure 2-3: Sample 3-dimensional acceleration traces from a typical participant in slip, trip and faint/collapse falling trial. Along the x-axis 1.5 seconds time reflects an approximate instance for pelvis impact.

A

Sensor location: Left Foot + Right Foot + Sternum

Classified as ⇨	**Slips (n = 48)**	**Trips (n = 48)**	**Other (n = 144)**
Slips	46	2	0
Trips	2	46	0
Other	1	5	138

B

For Slips

Classified ⇨	**Slips**	**Trips**	**Others**
Slips	TP	FN	FN
Trips	FP	TN	TN
Others	FP	TN	TN

For Trips

	Slips	**Trips**	**Others**
Slips	TN	FP	TN
Trips	FN	TP	FN
Others	TN	FP	TN

For Others

	Slips	**Trips**	**Others**
Slips	TN	TN	FP
Trips	TN	TN	FP
Others	FN	FN	TP

Figure 2-4: (A) Confusion matrix, representing results from the best marker combination. (B) Defining true positive (TP), true negative (TN), false positive (FP) and false negative (FN) for three types of falls.

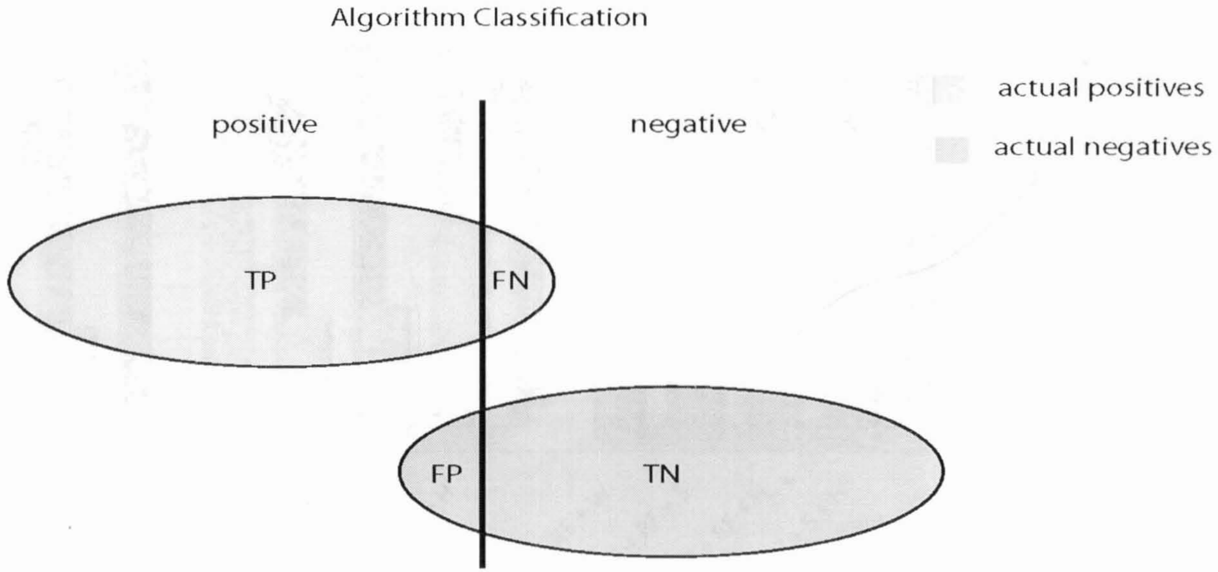


Figure 2-5: Graphical representation of various measures of performance in terms of true positive, true negative, false positive and false negative.

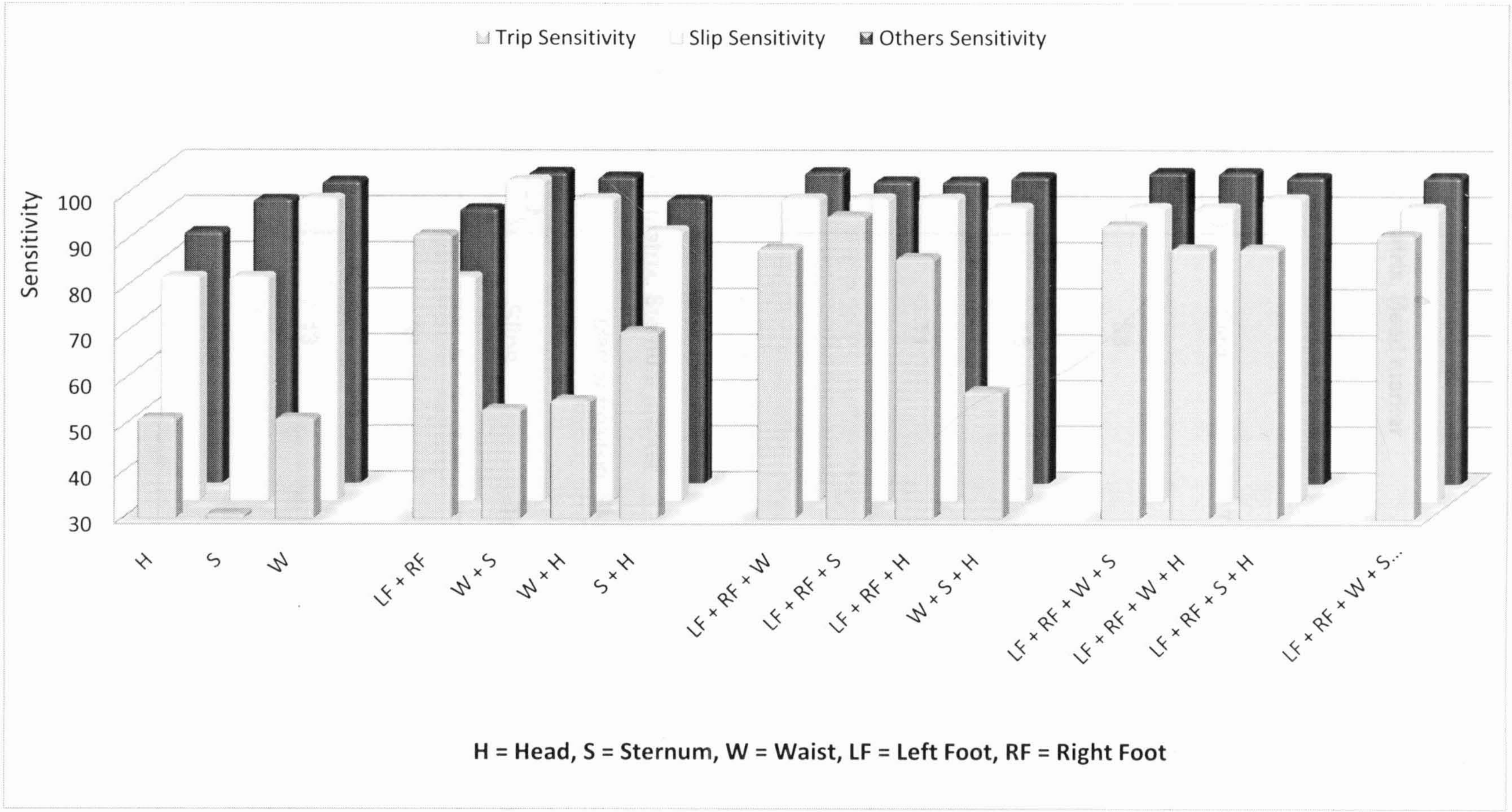


Figure 2-6: Sensitivity comparison for sensor combinations

2.7 Tables

Table 2-1: Confusion matrix, Head marker

Marker Position: Head

Classified as ⇨	Slips	Trips	Other causes
Slips	38	1	9
Trips	18	25	5
Other causes	11	11	122

Table 2-2: Confusion matrix, Sternum marker

Marker Position: Sternum

Classified as ⇨	Slips	Trips	Other causes
Slips	38	0	10
Trips	13	15	20
Other causes	11	1	132

Table 2-3: Confusion matrix, Waist marker

Marker Position: Waist

Classified as ⇨	Slips	Trips	Other causes	
Slips	46	1	1	
Trips	15	23	6	
Other causes	2	3	139	

Table 2-4: Confusion matrix, Left Foot + Right Foot

Marker Position: Left Foot + Right Foot

Classified as ⇨	Slips	Trips	Other causes	
Slips	38	5	5	
Trips	4	44	0	
Other causes	11	3	130	

Table 2-5: Confusion matrix, Waist + Sternum

Marker Position: Waist + Sternum

Classified as ⇨	Slips	Trips	Other causes
Slips	48	0	0
Trips	12	26	10
Other causes	0	3	141

Table 2-6: Confusion matrix, Head + Waist

Marker Position: Head + Waist

Classified as ⇨	Slips	Trips	Other causes
Slips	46	1	1
Trips	16	27	5
Other causes	1	3	140

Table 2-7: Confusion matrix, Sternum + Head

Marker Position: Sternum + Head

Classified as	Slips	Trips	Other causes
Slips	43	1	4
Trips	7	34	7
Other causes	2	10	132

Table 2-8: Confusion matrix, Left Foot + Right Foot + Waist

Marker Position: Left Foot + Right Foot + Waist

Classified as	Slips	Trips	Other causes
Slips	46	2	0
Trips	4	43	1
Other causes	2	1	141

Table 2-9: Confusion matrix, Left Foot + Right Foot + Sternum

Classified as ⇒	Marker Position: Left Foot + Right Foot + Sternum		
	Slips	Trips	Other causes
Slips	46	2	0
Trips	2	46	0
Other causes	1	5	138

Table 2-10: Confusion matrix, Left Foot + Right Foot + Head

Classified as ⇒	Marker Position: Left Foot + Right Foot + Head		
	Slips	Trips	Other causes
Slips	46	2	0
Trips	6	42	0
Other causes	3	2	139

Table 2-11: Confusion matrix, Sternum + Waist + Head

Classified as ⇨	Marker Position: Sternum + Waist + Head Slips	Trips	Other causes
Slips	45	1	2
Trips	17	28	3
Other causes	1	3	140

Table 2-12: Confusion matrix, Left Foot + Right Foot + Sternum + Waist

Marker Position: Left Foot + Right Foot + Sternum + Waist

Classified as ⇨	Slips	Trips	Other causes
Slips	45	2	1
Trips	3	45	0
Other causes	1	2	141

Table 2-13: Confusion matrix, Left Foot + Right Foot + Waist + Head

Classified as	Marker Position: Left Foot + Right Foot + Waist + Head Slips	Trips	Other causes
Slips	45	2	1
Trips	5	43	0
Other causes	2	1	141

Table 2-14: Confusion matrix, Left Foot + Right Foot + Sternum + Head

Classified as	Marker Position: Left Foot + Right Foot + Sternum + Head Slips	Trips	Other causes
Slips	46	2	0
Trips	5	43	0
Other causes	1	3	140

Table 2-15: Confusion matrix, Left Foot + Right Foot + Waist + Sternum + Head

Marker Position: Left Foot + Right Foot + Sternum + Waist + Head

Classified as	Slips	Trips	Other causes
Slips	45	2	1
Trips	4	44	0
Other causes	2	2	140

Table 2-16: Sensitivity, specificity, precision and accuracy of marker array in detecting the cause of falls

	Slips (n = 48)				Trips (n = 48)				Others (n = 144)			
Marker Combination	**Sens**	**Spec**	**Prec**	**Accu**	**Sens**	**Spec**	**Prec**	**Accu**	**Sens**	**Spec**	**Prec**	**Accu**
Head	79	85	57	84	52	93	67	85	85	85	90	85
Sternum	79	87	61	86	31	99	94	86	92	69	81	82
Waist	96	91	73	92	52	98	85	89	96	92	95	95
Left Foot + Right Foot	79	92	72	89	92	96	85	95	90	95	96	92
Waist + Sternum	100	94	80	95	54	98	90	89	98	89	93	94
Waist + Head	96	91	73	92	56	98	87	89	97	94	96	96
Sternum + Head	89	95	83	94	71	94	75	89	92	88	92	90
Left Foot + Right Foot + Waist	96	97	88	97	89	98	93	97	98	99	99	98
Left Foot + Right Foot + Sternum	96	98	94	98	96	96	87	96	96	100	100	97
Left Foot + Right Foot + Head	96	95	84	95	87	98	91	96	96	100	100	98
Waist + Sternum + Head	94	91	71	91	58	98	87	90	97	95	96	96
Left Foot + Right Foot + Waist + Sternum	94	98	92	97	94	98	92	97	98	99	99	98
Left Foot + Right Foot + Waist+ Head	94	96	86	96	89	98	93	97	98	99	99	98
Left Foot + Right Foot + Sternum + Head	96	97	88	97	89	97	89	96	97	100	100	98
Right Foot + Left Foot + Waist + Sternum + Head	94	97	88	96	92	98	92	97	97	99	99	98

Legend:-

$$\text{Sens (Sensitivity (\%))} = \frac{TP}{TP + FN} \times 100$$

$$\text{Spec (Specificity (\%))} = \frac{TN}{TN + FP} \times 100$$

$$\text{Prec (Precision (\%))} = \frac{TP}{TP + FP} \times 100$$

$$\text{Accu (Accuracy (\%))} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

3: CHAPTER 3
ACCURACY OF WEARABLE SENSORS FOR DISTINGUISHING FALLS CAUSED BY DIFFERENT WEIGHT SHIFTING ACTIVITIES

3.1 Introduction

Falls are the number one cause of injury in older adults. An accurate understanding of the cause and circumstances of falls is essential to guiding interventions at the level of the patient or population. Incident reports represent the primary mechanism for collecting information of fall mechanisms in long term care facilities (LTC). Such reports are completed by nursing staff who either interview the faller or witness, or perhaps witness the fall themselves. Current available statistics derived from incident reports and retrospective surveys suggest that approximately 50% of falls in the older adults are due to slips and trips (Berg et al., 1997; Cavanillas et al., 2000; Troy et al., 2006). However, the accuracy of these methods has been questioned (Cummings et al., 1988; Wei et al., 2001; Feldman, 2009). Recalling the mechanics of a fall event is challenging even for young adults (Feldman, 2009), and may be especially difficult for older adults with cognitive impairment, which is common in LTC residents. Furthermore, most falls, even in LTC, are un-witnessed (Hayes et al., 1993; Nurmi et al., 1996; Wagner et al., 2005). Therefore, to understand the causes of falls and formulate effective fall prevention strategies, researchers, clinicians and policy makers cannot rely solely on conventional methods and new techniques are required to reliably detect and provide information on the cause of falls in older adults.

Wearable inertial sensors have received increasing attention by researchers interested in developing accurate methods for monitoring mobility and falls. Due to rapid progress in miniaturization and decreasing costs, the range of applications for such systems has expanded to fields including automobile and avionics, animation and photography, computers and telecommunications and health and safety. In recent years, as the public health importance of falls in older adults has received increased recognition, numerous studies have examined the potential of wearable inertial sensors (accelerometer, gyroscopes, tilt sensors etc.) to detect falls (Lindemann et al., 2005; Bourke et al., 2006; Chen et al., 2005; Quagliarella et al., 2008; Noury et al., 2003; Bourke, et al., 2008; Nyan et al., 2006; Wu et al., 2008; Hwang et al., 2004; Noury et al., 2008). However, in addition to detecting falls (which is important for alerting health providers or family members about the event), wearable sensor systems offer the potential to provide information on the cause of the fall and the physiological mechanisms contributing to the event.

In chapter 2, I showed that a wearable sensor system consisting of 3D acceleration of three sensors (at the feet and sternum) was able to distinguish with 96% sensitivity the causes of falls due to slips, trips and “other causes”. In the current study, I extend this line of inquiry to examine the utility of such systems for distinguishing between the five individual sub-cases of “other falls”: i) fainting, ii) incorrect transfer of weight while sitting down on a chair (IT-sitting), iii) incorrect transfer of weight while standing up from sitting (IT-rising), iv) reaching, and v) turning. I addressed this goal by conducting “falling experiments” with young adults and acquiring whole-body kinematic data from a 3D motion analysis system. I then input acceleration data into a linear discriminant analysis classification routine to examine how the location and number of acceleration sensors influence the accuracy of the system in distinguishing the above-mentioned five types of falls. This study contributes to the development of an automatic, wearable system to complement conventional methods to gather information on the cause and circumstances of falls in older adults.

3.2 Material and methods

3.2.1 Participants

Sixteen young healthy subjects (12 male; 4 female) participated in the experiment, ranging in age from 20 to 35 years (mean = 25.6 yrs, SD = 3.8). Safety precautions prevented us from including older adults in our falling trials. All subjects were undergraduate or graduate students at Simon Fraser University, recruited through advertisements posted on university notice boards. All participants provided informed written consent, and the experiment protocol was approved by the Research Ethics Committee at Simon Fraser University.

3.2.2 Experiment Protocol

During the experiment, five different types of falls were simulated (Figure 3-1), all of which resulted in impact on a 30 cm thick gymnasium mat: i) fainting or syncope; ii) incorrect transfer while sitting on a chair (IT-sitting); iii) incorrect transfer while rising from an initial sitting position (IT-rising), iv); reaching for an object below knee height; and v) turning 180°. Prior to the start of the experiment, each subject was shown specific videos from our records of real life falls in older adults due to the aforementioned five other causes. In addition, trials with subjects walking normally for approximately 5 meters, were also conducted. The sequence of presentation of the various fall types was randomized across subjects to minimize the effect of fatigue or learning on fall behaviour.

In fainting trials, subjects 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. No instruction was given about the direction of the fall. In falls due to incorrect transfer while sitting, I 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. In falls due to incorrect transfer while rising, subjects initially sat on a chair and were instructed to lose their balance while attempting to stand up. No instruction was provided on the fall direction. In falls caused by reaching, subjects 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. In falls due to turning, subjects were instructed to turn 180 degrees from standing, lose balance and fall. Again, no instruction was provided on the desired fall direction.

Each subject underwent three trials in each of the five conditions. Therefore, from sixteen subjects I collected a total of 48 trials for each category.

3.2.3 Data collection

During the trials, I used an eight camera motion analysis system (Eagle system, Motion Analysis Corp.) to acquire three-dimensional position data at 120 Hz from 22 reflective skin markers. Markers were located bilaterally on the lateral malleolus, lateral epicondyle of the femur, greater trochanter, anterior superior iliac spine, acromion, lateral epicondyle of the humerus, dorsal surface of the hand and scapula, and at the sternum, C7 vertebrae, sacrum and at the front, back and top of the head. Position data were then low pass filtered using a recursive butterworth filter (4^{th} order, cutoff frequency = 20Hz) and double differentiated to estimate accelerations.

3.3 Data Analysis

Data analysis focused on determining whether the cause of falls could be accurately predicted from 3D acceleration data from five key anatomical locations (left foot, right foot, waist, sternum and head), selected based on their feasibility for sensor placement on the human body. For each trial, I inspected motion data to determine the approximate instant when the pelvis first impacted the ground. Acceleration data, for the 1500 milliseconds preceding pelvis impact (Figure 3-2) were input to my fall classification algorithm, showed subtle changes in acceleration profiles across various fall types. For example – peak accelerations observed from the waist marker in the z-axis reflected the occurrence and instant of falls (pelvis impact). Similarly, in this particular trial, the sternum marker showed similar traces of acceleration while simulating falls due to reaching and turning. However, waist marker provided distinct acceleration profiles in falls due to IT-rising as opposed to the other four fall types.

Therefore, for the classification of the above-mentioned five types of falls, I calculated the mean and variance of the five markers' X, Y and Z acceleration traces over the 1500 ms preceding pelvis impact. These outcomes resulted in a 30 dimensional "feature vector". Based on the assumption that the feature vectors from the three fall types were linearly separable, I used Linear Discriminant Analysis (LDA) using Fisher's criterion to classify the causes of falls. In the procedure, I split the feature vector into training and testing sets of equal size by choosing data from the first eight subjects for training and the following eight for testing. The procedure LDA transforms a classification problem from a higher to lower dimensional feature space through a set of projection operations, which results in optimal separability among different classes (Baudat and Anouar, 2000; Muller et al., 2001). To classify two or more sets of data, this can be achieved by maximizing the following ratio of between-class scatter divided by within-class scatter:

$$J(w) = \arg max_{w} \left(\frac{w^T S_b w}{w^T S_w w} \right)$$

where "w" is a linear transform, "S_b" is the between class variance, "S_w" is the within class variance, and "$argmax_w$" refers to maximizing the above equation. The generalization of the within-class scatter "S_w" and the between-class scatter "S_b" for "K" classes are given by the following expression:

$$m_k = \frac{1}{|N_k|} \sum_{n \in C_k} x_n ,$$

$$\mu = \frac{1}{N} \sum_{k=1}^{K} N_k \, \mu_k \ ,$$

$$S_w = \sum_{k=1}^{K} \sum_{n \in C_k} (x - m_k)(x - m_k)^T \ ,$$

and

$$S_b = \sum_{k=1}^{K} N_k (m_k - \mu) \, (m_k - \mu)^T.$$

Here m_k is the sample mean for the k^{th} class, N_k is the number of patterns in class C_k, $|N_k|$ indicates the number of vectors in the k^{th} class and $N = \sum_k N_k$ in the total number of data points (Bishop, 2006).

I conducted linear discriminant analysis using acceleration data from each marker, and for each possible combination of 2, 3, 4 and 5 markers. In each case, I then constructed confusion matrices (Tables 3-1 to 3-15) and used these to calculate sensitivity and specificity as follows:

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \text{ and}$$

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100.$$

Where TP = true positive, FN = false negative, FP = false positive, and TN = true negative.

For each number of markers (ranging from one to five), I ranked the performance of a given marker location, or combination of markers, based on the number of fall categories for which it provided the highest sensitivity. Note that this is a departure from the performance ratings used in Chapter 2, which were based on minimal sensitivity across conditions and was deemed more suitable for the larger number of conditions examined here.

3.4 Results

With a single marker, the best classification was achieved by the head marker (Table 3-1) which provided maximum sensitivities in identifying four out of six conditions, followed by the waist marker, which provided the best sensitivity for classifying three of the six conditions. The head marker successfully identified walking trials from other fall causes with 100% sensitivity. Similarly, the head marker was found to be the most sensitive in detecting falls due to IT-sitting (42% sensitive), reaching (62% sensitive) and turning (67% sensitive). However, the head marker, was least effective in identifying IT-rising (46% sensitive), which were better classified by the sternum and waist markers. The waist marker was most effective in classifying falls due to fainting (33% sensitive), IT-rising (83% sensitive), and turning (67% sensitive), but showed 92% sensitivity in identifying walking from other fall causes. The sternum marker was least effective in identifying falls due to faints (17% sensitive), IT-sitting (17% sensitive), reaching (33% sensitive) and turning (58% sensitive).

With two markers, the best combination was that of head + waist, which also provided maximum sensitivities in four conditions. The marker combination of head + waist was most effective in classifying walking (100% sensitive), IT-rising (83% sensitive), reaching (67% sensitive) and turning (75% sensitive), but was least effective in identifying falls due to faints (33% sensitive). Among the two markers combinations, the combination of left foot + right foot provided the highest sensitivities in detecting faints (62% sensitive) and IT-rising (83%

sensitive). However, it was less successful than other combinations in detecting walking, IT-sitting and reaching (with 83%, 29% and 50% sensitivities, respectively). Similarly, the sternum + head markers combination was most effective in identifying walking (100% sensitive) and IT-sitting (50% sensitive), and least effective in detecting IT-rising (75% sensitive) and turning (67% sensitive). In the group of two-marker combinations, the waist + sternum combination was the least accurate and provided the lowest sensitivities in detecting all five causes of falls.

With three markers, the best combination was achieved by placing markers on left foot, right foot and head, which provided maximum sensitivities in four conditions: walking (100%) and falls due to fainting (67%), IT-sitting (59%) and reaching (67%). Similarly, the three-marker combination of left foot + right foot + waist was most effective in detecting falls due to faints (67% sensitive), IT-rising (87% sensitive) and turning (79% sensitive). On the other hand, it was least successful in identifying falls due to IT-sitting and reaching, with sensitivities of 37% and 54%, respectively. The waist + sternum + head combination successfully detected walking and IT-rising with 100% and 83% sensitivities, respectively, it was least effective in classifying falls due to faints (29% sensitive), IT-sitting (50% sensitive) and turning (62% sensitive).

With four markers, the best marker combination was that of left foot + right foot + waist + head, which provided the highest sensitivity in classifying walking and all other five causes of falls. Apart from IT-sitting (where the combination provided 54% sensitivity), all other conditions were detected with at least 71% sensitivity.

The five-marker combination of left foot + right foot + waist + sternum + head was found superior to all other marker combinations. This particular combination provided 100% sensitivity in walking trials, 71% and 62% sensitivities in detecting falls due to faints and IT-sitting and, 92%, 71% and 79% sensitivities in classifying IT-rising, reaching and turning.

3.5 Discussion

In the current study, I conducted laboratory based falling experiment to examine the utility of a wearable sensor array for distinguishing the causes of falls due to fainting or syncope, incorrect weight transfer while sitting down on a chair and rising from sitting, reaching for an object and turning. Three dimensional acceleration data from the 1.5 seconds preceding pelvis impact from five markers (mounted at left foot, right foot, waist, sternum and head) were entered into a linear discriminant model to identify the accuracy of single markers as well as combinations of 2, 3, 4 and 5 markers in distinguishing falls due to the aforementioned five causes.

In the study described in Chapter 2, I used a slightly different criterion based on the minimum observed sensitivity, to rank marker combinations. I found that three dimensional acceleration data from the three marker combination left foot + right foot + sternum when put into a linear discriminant analysis, provided at least 96% sensitivity in distinguishing falls due to slips and trips from the five types of “other falls”, examined in greater detail in the current study. In this study, I had six conditions (one walking and five falls due to “other causes”) which were required to be classified. Therefore, in evaluating performance, I considered a specific marker combination to be the best if it scored the highest sensitivities in the greater number of conditions classifying the most conditions.

Based on this criterion, I found that the best location for a marker was at the head, which provided the best sensitivity in four conditions walking (100% sensitive), IT-sitting (42% sensitive), reaching (62% sensitive) and turning (62% sensitive). Similarly, the best two-marker combination (of waist + head), and the best three marker combination (of left foot + right foot + head) was most sensitive in identifying four conditions. Among all four-marker combinations, the one including left foot + right foot + waist + head markers showed the best sensitivities in all six conditions, and was as sensitive as the five-marker combination for all conditions except IT-sitting (where the five-marker combination showed a slightly higher sensitivity of 62% as opposed to 54%).

However, even with the best five-marker combination, the LDA technique provided a minimal sensitivity of only 62% in distinguishing other causes of falls. This reflects that acceleration data from the five fall types were not entirely linearly separable. Of particular note is the modest sensitivity of the algorithm (at best 62%) for classifying falls due to IT-sitting and reaching for an object below knee height, which exhibit similar whole-body kinematics. Modest sensitivity was also observed for falls due to fainting which were often confused with falls due to reaching. In contrast to falls due to fainting, IT-sitting and reaching, the LDA technique was considerably more accurate in classifying walking trials and falls due to IT-rising and turning. As in the case for slips and trips examined in Chapter 2, this is primarily due to unique kinematic features of these falls (Figures 3-1 and 3-2).

While my data analysis focused primarily on sensitivity, Table 3-2 also presents specificities which were, for many fall causes, close to 100% for all marker combinations. This reflects that false positives were generally less frequent than false negatives. A specificity of 100% means that the test recognizes all actual negatives - for example in detecting "walking", system does not identify any of the five other fall causes (fainting, IT-sitting, IT-rising, reaching and turning) as walking.

As in the study described in Chapter 2, there are important limitations to this study. First, all falls were performed under controlled laboratory conditions by healthy individuals between the age 20 and 35 years. There are inevitable discrepancies between the falls of these young individuals and older adults. However, a strength of my study was the utilization of video segments of real life falls of older adults in training sessions. Secondly, this study did not focus on fall detection, but rather determining causes of falls based on acceleration data 1.5 seconds prior to pelvis impact. However, previous research shows that the same markers, as included in my study (waist and sternum), can be used to detect an occurrence of a fall (Wu 2000; Lindemann et al., 2005; Bourke et al., 2006; Chen et al., 2005 and Noury et al., 2003) with high accuracy. Third, my analyses was restricted to the use of linear discriminant analysis (with Fisher's criterion) to classify falls from acceleration data. Additional studies are required to examine the potential improvements provided by other linear and non-linear classification techniques, such as Support Vector Machine (SVM) models or Gaussian and Hidden Markov Models (HMM) to distinguish the cause of falls examined here.

In summary, I found that data from an array of up to five wearable 3D acceleration sensors, input to an LDA classification scheme, provided reasonable sensitivity (of at least 79%) in classifying falls due to loss of balance during rising and turning, but less successful in classifying falls during sitting, fainting or reaching. Future work should examine the utility of alternative classification methods, and different sensor technologies, such as gyroscopes (which provide measure of angular velocity of limb segments), for classifying the falls of interest in this study. It remains possible, however, that specific types of falls, such as faints, cannot be easily classifies based only on kinematics, and physiological data regarding blood pressure or muscle activity (from electromyographic surface electrodes) are essential components to kinematic information in detecting such causes.

3.6 Figures

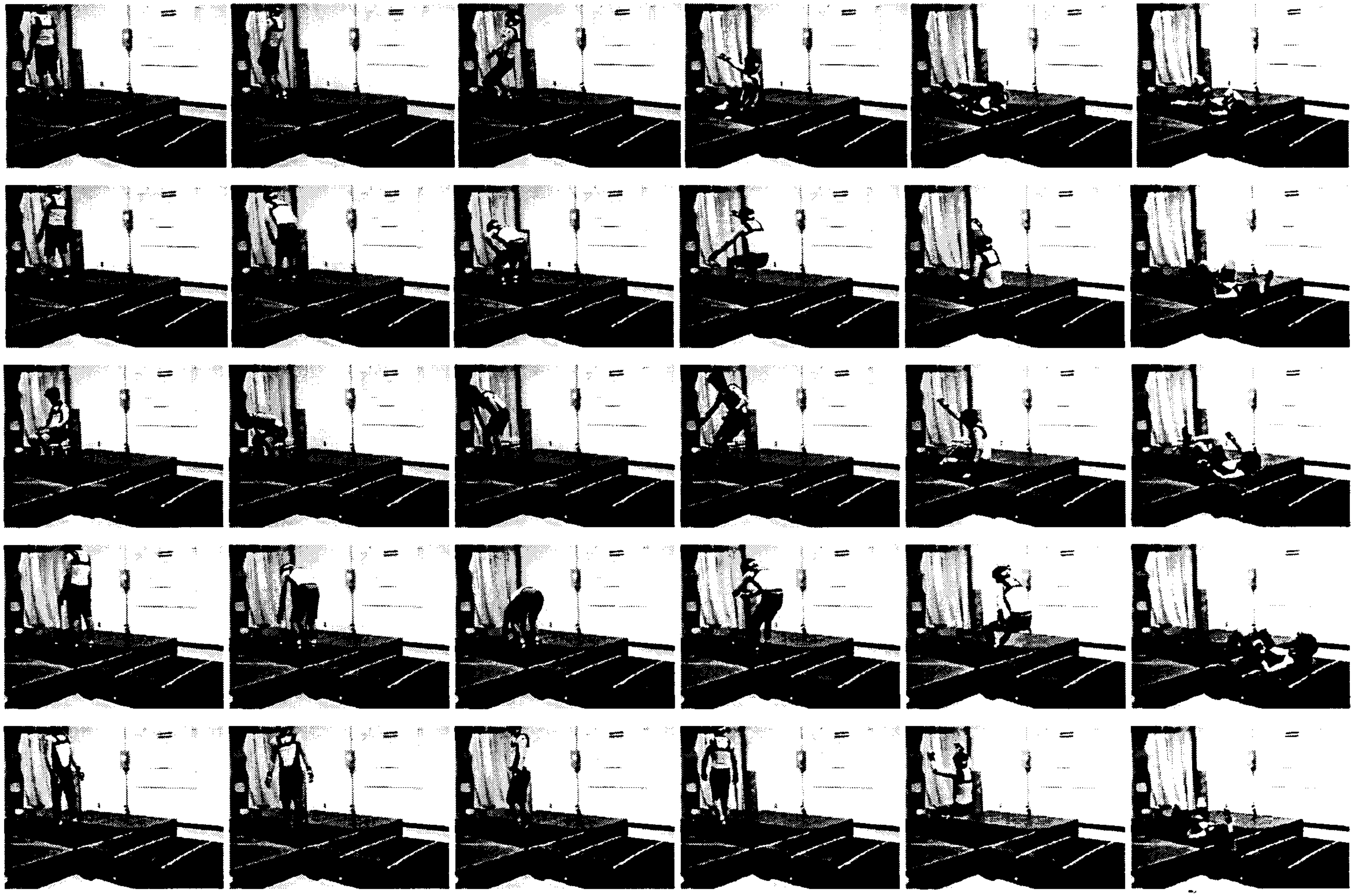
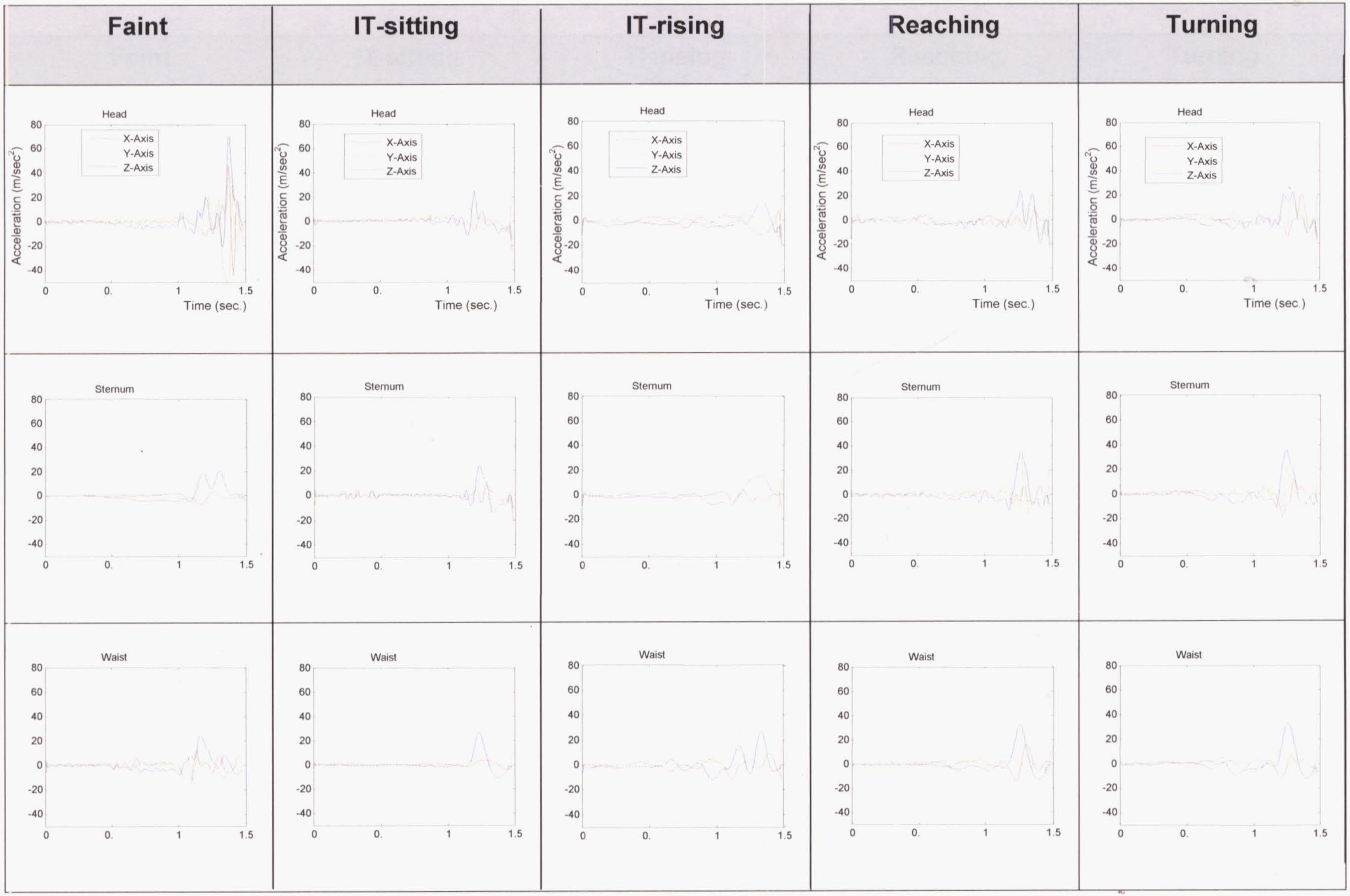


Figure 3-1: Simulation of falls due to fainting, incorrect transfer while sitting (IT-sitting), incorrect transfer while rising (IT-rising), reaching and turning.


Faint
IT-sitting
IT-rising
Reaching
Turning
Head
Sternum
Waist
X-Axis
Y-Axis
Z-Axis
Acceleration (m/sec^2)
Time (sec.)

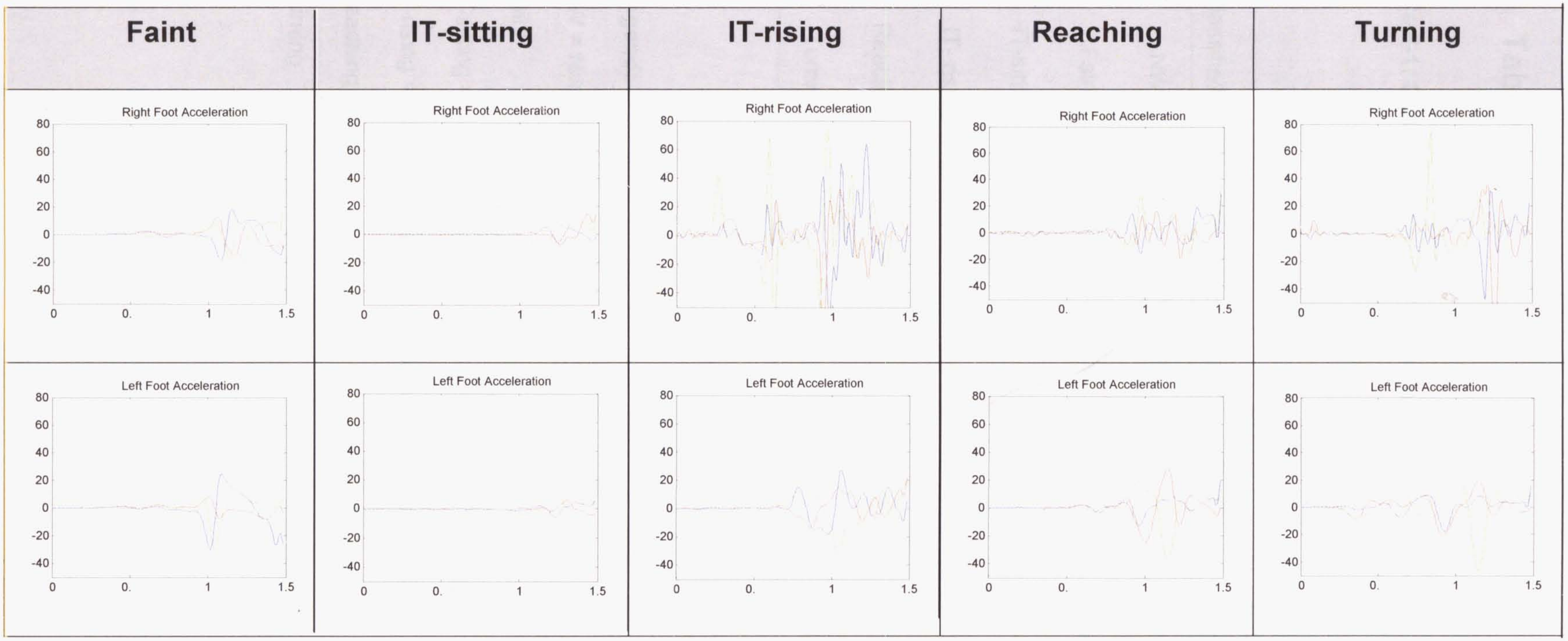


Figure 3-2: Sample 3-dimensional acceleration traces from a typical participant in falls due to fainting, IT-sitting, IT-rising, reaching and turning. On the time scale, 1.5 seconds represents and approximate instant of pelvis impact.

3.7 Tables

Table 3-1: Confusion matrix, Head marker

	Marker Position: Head					
Classified as →	NW	Faint	IT-sitting	IT-rising	Reaching	Turning
NW	24	0	0	0	0	0
Faint	0	6	7	3	2	6
IT-sitting	1	2	10	0	2	9
IT- rising	1	8	1	11	2	1
Reaching	0	0	2	2	15	5
Turning	0	0	2	3	3	16

Legend:

NW = Normal Walk

Faint

IT-sitting = Incorrect Transfer of body weight while Sitting

IT-rising = Incorrect Transfer of body weight while Standing

Reaching

Turning

Table 3-2: Confusion matrix, Sternum marker

Marker Position: Sternum

Classified as →	NW	Faint	IT-sitting	IT-rising	Reaching	Turning
NW	**23**	**1**	**0**	**0**	**0**	**0**
Faint	**0**	**4**	**7**	**7**	**4**	**2**
IT-sitting	**2**	**7**	**4**	**2**	**0**	**9**
IT- rising	**1**	**3**	**1**	**12**	**3**	**3**
Reaching	**0**	**1**	**5**	**2**	**8**	**8**
Turning	**1**	**3**	**0**	**1**	**5**	**14**

Table 3-3: Confusion matrix, Waist marker

Marker Position: Waist

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	22	2	0	0	0	0
Faint	0	8	1	4	2	9
IT-sitting	0	7	8	1	5	3
IT- rising	0	1	2	20	0	1
Reaching	1	0	4	3	12	4
Turning	0	7	0	0	1	16

Table 3-4: Confusion matrix, Left foot + Right foot

Marker Position: Left Foot + Right Foot

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	20	0	3	0	0	1
Faint	0	15	2	0	5	2
IT-sitting	2	2	7	1	9	3
IT- rising	0	2	1	20	0	1
Reaching	0	4	4	0	12	4
Turning	1	1	2	0	3	17

Table 3-5: Confusion matrix, Waist + Sternum

Marker Position: Waist + Sternum

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	23	1	0	0	0	0
Faint	2	8	1	3	3	7
IT-sitting	0	9	7	0	1	7
IT- rising	0	1	2	18	2	1
Reaching	0	0	5	3	12	4
Turning	0	4	2	0	2	16

Table 3-6: Confusion matrix, Head + Waist

Marker Position: Head + Waist

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	24	0	0	0	0	0
Faint	0	8	3	3	3	7
IT-sitting	0	4	9	2	1	8
IT- rising	0	1	2	20	0	1
Reaching	0	0	2	2	16	4
Turning	0	3	1	0	2	18

Table 3-7: Confusion matrix, Sternum + Head

Marker Position: Sternum + Head

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	24	0	0	0	0	0
Faint	0	9	2	4	3	6
IT-sitting	0	4	12	0	1	7
IT- rising	1	2	2	18	1	0
Reaching	0	1	3	2	13	5
Turning	1	1	2	1	3	16

Table 3-8: Confusion matrix, Left foot + Right foot + Waist

Classified as →	Marker Position: Left Foot + Right Foot + Waist					
	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	23	0	0	0	0	1
Faint	0	16	1	0	5	2
IT-sitting	0	3	9	2	7	3
IT- rising	0	0	2	21	0	1
Reaching	0	4	3	0	13	4
Turning	0	2	3	0	0	19

Table 3-9: Confusion matrix, Left foot + Right foot + Sternum

Classified as →	Marker Position: Left Foot + Right Foot + Sternum					
	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	23	1	0	0	0	0
Faint	1	16	2	0	5	0
IT-sitting	1	3	11	1	4	4
IT- rising	0	2	1	20	0	1
Reaching	0	3	4	0	11	6
Turning	0	1	2	0	3	18

Table 3-10: Confusion matrix, Left foot + Right foot + Head

Marker Position: Left Foot + Right Foot + Head

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	24	0	0	0	0	0
Faint	0	16	2	0	4	2
IT-sitting	2	2	13	1	4	2
IT- rising	0	2	1	20	0	1
Reaching	0	2	2	1	16	3
Turning	0	0	2	1	3	18

Table 3-11: Confusion matrix, Waist + Sternum + Head

Marker Position: Sternum + Waist + Head

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	24	0	0	0	0	0
Faint	0	6	2	4	3	9
IT-sitting	0	6	12	1	0	5
IT- rising	0	1	3	20	0	0
Reaching	0	0	5	1	14	4
Turning	0	3	3	0	3	15

Table 3-12: Confusion matrix, Left foot + Right foot + waist + Sternum

Marker Position: Left foot + Right foot + Waist + Sternum

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	22	2	0	0	0	0
Faint	0	16	1	0	4	3
IT-sitting	0	4	10	2	6	2
IT- rising	0	0	2	22	0	0
Reaching	0	2	3	0	15	4
Turning	0	2	2	0	2	18

Table 3-13: Confusion matrix, Left foot + Right foot + Waist + Head

Marker Position: Left foot + Right foot + Waist + Head

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	24	0	0	0	0	0
Faint	0	17	1	0	4	2
IT-sitting	0	2	13	1	3	5
IT- rising	0	0	1	22	0	1
Reaching	0	2	3	1	17	1
Turning	0	2	2	0	1	19

Table 3-14: Confusion matrix, Left foot + Right foot + Sternum + Head

Marker Position: Left foot + right foot + Sternum + Head

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	22	2	0	0	0	0
Faint	0	16	1	0	4	3
IT-sitting	0	4	10	2	2	6
IT-rising	0	0	2	22	0	0
Reaching	0	2	4	0	14	4
Turning	0	2	2	0	2	18

Table 3-15: Confusion matrix, Left foot + Right foot + Waist + Sternum + Head

Marker Position: Left foot + Right foot + Waist + Sternum + Head

Classified as →	NW	Faint	IT-sitting	IT- rising	Reaching	Turning
NW	24	0	0	0	0	0
Faint	0	17	1	0	4	2
IT-sitting	0	1	15	1	4	3
IT-rising	0	0	1	21	0	1
Reaching	0	1	5	0	17	1
Turning	0	3	2	0	0	19

Table 3-16: Sensitivity and specificity of marker array in detecting the cause of falls.

	Walking (24)		Faint (24)		IT-sitting (24)		IT- rising (24)		Reaching(24)		Turning (24)	
Marker Combination	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**	**Sens**	**Spec**
Head	100	98	25	92	42	90	46	93	62	92	67	82
Sternum	96	96	17	87	17	89	50	90	33	90	58	82
Waist	92	99	33	86	33	94	83	93	50	93	67	86
Left Foot + Right Foot	83	97	62	92	29	90	83	99	50	86	71	91
Waist + Sternum	96	98	33	87	29	92	75	95	50	93	67	84
Waist + Head	100	100	33	93	37	93	83	94	67	95	75	83
Sternum + Head	100	98	37	93	50	92	75	94	54	93	67	85
Left Foot + Right Foot + Waist	96	100	67	92	37	92	87	98	54	90	79	91
Left Foot + Right Foot + Sternum	96	98	67	92	46	92	83	99	56	90	75	91
Left Foot + Right Foot + Head	100	98	67	95	54	94	83	97	67	91	75	93
Waist + Sternum + Head	100	100	25	92	50	89	83	95	58	95	62	85
Left Foot + Right Foot + Waist + Sternum	92	100	67	92	42	93	92	98	62	90	75	92
Left Foot + Right Foot + Waist+ Head	100	100	71	95	54	94	92	98	71	93	79	92
Left Foot + Right Foot + Sternum + Head	92	100	67	92	42	92	92	98	58	93	75	89
Right Foot + Left Foot + Waist + Sternum + Head	100	100	71	96	62	92	92	99	71	93	79	94

Legend:

$$Sens\ (Sensitivity\ (\%)) = \frac{True\ Positive}{True\ Positive + False\ Negative} \times 100 \qquad Spec\ (Specificity\ (\%)) = \frac{True\ Negative}{True\ Negative + False\ Positive} \times 100$$

4: CHAPTER 4
THESIS SUMMARY AND CONCLUSION

The primary goal of my master thesis was to develop and evaluate a system for automatic detection of the cause of a fall using wearable sensors. I further analysed how the location and the number of sensors affected the system's performance in distinguishing between various causes of falls.

In my first study (Chapter 2), I conducted laboratory experiments with young adults who simulated various types of falls, observed through video capture in the daily life of older adults. These included falls due to slips, trips and other causes (fainting or syncope, incorrect transfer or shifting of body weight during the trials, kinematic data were recorded with a video based motion capture system. Means and variances of the acceleration data from each of five locations (head, sternum, right ASIS, left ASIS and lateral malleoli) for the 1500 milliseconds preceding pelvis impact were calculated. Based on the assumption that the acceleration data from different types of falls are linearly separable, I used Linear Discriminant Analysis (LDA) to classify the causes of falls into three groups of slips, trips and other. My results confirmed the linear separability of the acceleration data from these three fall types. In particular, I observed at least

96% sensitivity in correctly classifying these causes of falls using only three sensors, optimally located at the left foot, right foot, and sternum. I also observed that classification sensitivity was no better with four and five markers than with three. Hence, I conclude that my linear discriminant analysis technique can accurately identify the aforementioned three causes of falls with as few as three markers, located at the ankles and sternum.

In my second study (Chapter 3), I examined whether similar acceleration data and LDA technique could correctly classify falls (acquired in the same experiment as described above) due to fainting or syncope, incorrect transfer while sitting down and standing up from a chair, reaching and turnings. My results indicated that, unlike slips, trips and all "other causes" combined, the acceleration data from each of these "other causes" were less linearly separable from each other. For example linear discriminant analysis using the most effective marker combination left foot + right foot + waist + sternum + head was only 62% sensitive in distinguishing falls due to incorrect transfer while sitting.

4.1 Future directions

This project contributes to improving our understanding of the cause and circumstances of falls in the high risk older population through the development of innovative wearable technologies. In particular, I showed that Linear Discriminant Analysis (LDA) is an effective technique for identifying falls due to slips, trips and other causes (Chapter 2). However, as described in Chapter 3, the LDA technique was considerably less accurate in distinguishing falls due to faint/collapse, incorrect transfer while sitting down and rising from a chair, and loss of balance when reaching and turning. To achieve high separability between these fall causes, alternative data classification schemes should be tested, such as support vector machine (SVM) approaches or Gaussian and Hidden Markov Models (HMM), should be tested. Furthermore, alternative sensing technologies, such as angular rate gyros or position – measuring magnetometers, should be considered as components to linear acceleration sensors.

By providing objective information on the cause of falls, and alleviating the need for health providers to rely on (often inaccurate) self – recall or witness reports of fall circumstances, my wearable sensor system has considerable value to clinicians and researchers in the area of fall prevention. In the future, this technology should be expanded to provide more comprehensive information on fall mechanics and be integrated with comprehensive physiological measures (e.g. electromyograms), blood pressure and electrocardiogram) for more detailed analysis of fall causation.

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