Ambulatory Fall Event Detection with Integrative Ambulatory Measurement (IAM) Framework

Jian Liu

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Graduate Committee Members:

Dr. Thurmon E. Lockhart, Chair
Dr. John Casali
Dr. Kari Babski-Reeves
Dr. Tom Martin

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This dissertation is dedicated to

my father

who helped me start the journey; I wish you were here to see my success

my mother

simply the best in the world; nothing would be possible without your support

Dr. Thurmon E. Lockhart

a great advisor for six years; a mentor and a friend for a lifetime

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ABSTRACT

Injuries associated with fall accidents pose a significant health problem to society, both in terms of human suffering and economic losses. Existing fall intervention approaches are facing various limitations. This dissertation presented an effort to advance indirect type of injury prevention approach. The overall objective was to develop a new fall event detection algorithm and a new integrative ambulatory measurement (IAM) framework which could further improve the fall detection algorithm's performance in detecting slip-induced backward falls. This type of fall was chosen because slipping contributes to a major portion of fall-related injuries. The new fall detection algorithm was designed to utilize trunk angular kinematics information as measured by Inertial Measurement Units (IMU).

Two empirical studies were conducted to demonstrate the utility of the new detection algorithm and the IAM framework in fall event detection. The first study involved a biomechanical analysis of trunk motion features during common Activities of Daily Living (ADLs) and slip-induced falls using an optical motion analysis system. The second study involved collecting laboratory data of common ADLs and slip-induced falls using ambulatory sensors, and evaluating the performance of the new algorithm in fall event detection.

Results from the current study indicated that the backward falls were characterized by the unique, simultaneous occurrence of an extremely high trunk extension angular velocity and a slight trunk extension angle. The quadratic form of the two-dimensional discrimination function showed a close-to-ideal overall detection performance (AUC of ROC[a] = 0.9952). The sensitivity, specificity, and the average response time associated with the specific configuration

of the new algorithm were found to be 100%, 95.65%, and 255ms, respectively. The individual calibration significantly improved the response time by 2.4% (6ms).

Therefore, it was concluded that slip-induced backward fall was clearly distinguishable from ADLs in the trunk angular phase plot. The new algorithm utilizing a gyroscope and orientation sensor was able to detect backward falls prior to the impact, with a high level of sensitivity and specificity. In addition, individual calibration provided by the IAM framework was able to further enhance the fall detection performance.

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Chapter 1

1. INTRODUCTION

1.1. Rationale

1.1.1. Existing fall intervention approaches and their limitations

Falls are the leading cause of injury deaths among people 65 years and older. Accidents are the fifth leading cause of death in older adults (after cardiovascular, neoplastic, cerebrovascular, and pulmonary causes), and falls constitute two-thirds of these accidental deaths. The National Safety Council reported that in 2005, 17,700 Americans met their death by falling, and of these deaths, the majority (over 80%) were people over 65 years of age (National Safety Council, 2006). Among all the causes leading to falls, foot slippage was found to contribute to between 40 and 50% of fall-related injuries (Courtney, Sorock, Manning, Collins, & Holbein-Jenny, 2001). Slipping was considered as the most frequent unforeseen trigger leading to the majority (55%) of the falls on the same level (Swedish Work Environment Authority and Statistics Sweden, 2000).

In addition to physical injury, falls can also have psychological and social consequences. Fear of falling and post-fall anxiety syndrome is recognized as negative consequences of falls. The loss of self-confidence to ambulate safely can result in self-imposed functional limitations and can lead to total helplessness and a loss of independence.

There may be simple measures that could reduce the incidence of falls without the need for physical restraints, sedation, excessive supervision, or other measures that undermine an individual's dignity and independence. Various researchers have identified risk factors that have a potential to predict falls in the elderly population, thus suggesting preventability.

The intervention programs for fall accidents can be classified in several ways. From the perspective of whether to prevent fall accidents (i.e. fall-prevention) from occurring or to mediate the injury (i.e. injury-prevention) caused by the fall accidents, current approaches to fall intervention can be categorized into *fall prevention* and *injury prevention.* A schematic illustration of widely accepted fall intervention programs is presented in Figure 1.

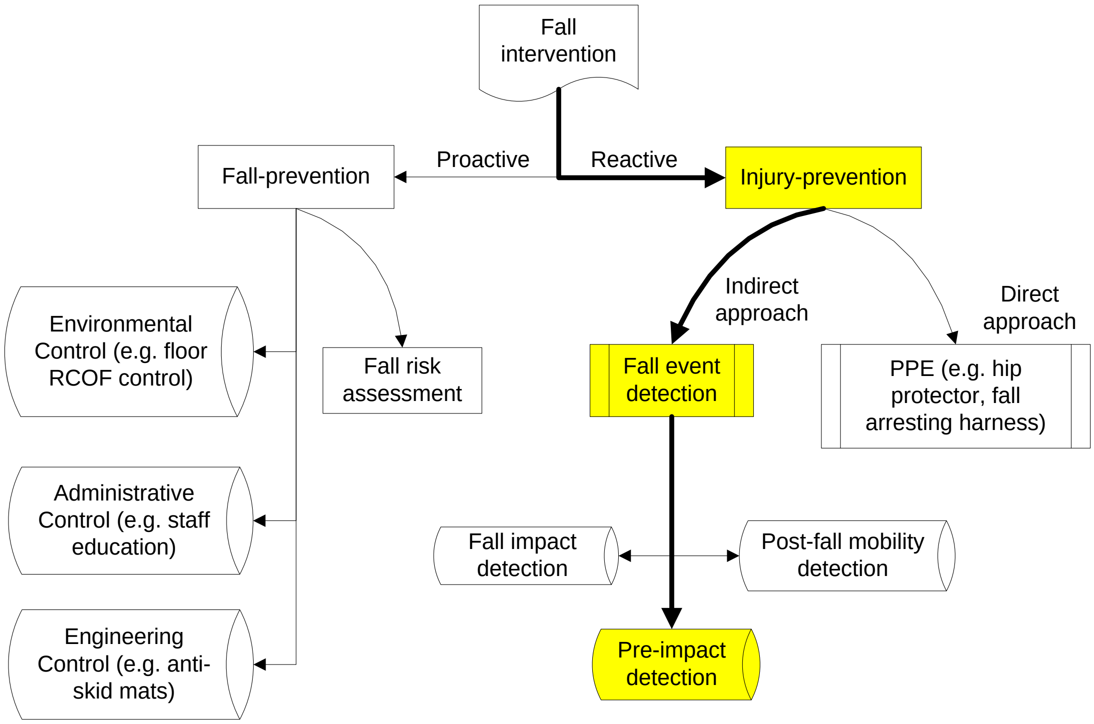

Figure 1 - Illustration of existing fall intervention solutions (RCOF: Required Coefficient of Friction)

Fall-prevention strategies seek to prevent the occurrence of future falls, mostly through means of environmental, administrative and engineering controls. These solutions include home environment modifications (e.g. lighting condition, floor surface condition, etc.), staff education programs (e.g. hazard awareness of nursing home staff), advice on medication use, and exercise with strength and balance training. Benefits of these solutions have been demonstrated (A. J. Campbell, Robertson, Gardner, Norton, & Buchner, 1999; J. Close, et al., 1999).

Although much research has been performed in this area, the existing fall-prevention strategies are far from effective. In terms of environmental control, it is agreed that maintaining an adequate level of floor coefficient of friction (COF) is important in preventing slip-induced fall accidents (Gronqvist, et al., 2001). However, the scientific community has not been able to reach a consensus on the safe level of floor COF and lacks a standard measurement method for floor COF (Courtney, Chang, Gronqvist, & Redfern, 2001). In terms of strength and balance training to reduce fall accidents among the elderly, the optimal training requirements, in terms of types of exercises and duration/intensity of exercises, are lacking and remain unclear. Furthermore, certain risk factors (e.g. aging) of fall accidents can hardly be modified by any preventive strategies.

Besides the above mentioned limitations associated with fall-prevention strategies, there is a fundamental issue with any fall-prevention program: even the most effective program cannot prevent fall accidents from happening altogether. Therefore, in the case of unavoidable fall accidents, it is critical to employ effective injury-prevention strategies. Injury-prevention strategies aim at reducing the impact and consequences of fall-related injuries mostly attained through personal protective equipment (PPE). PPE prevents/reduces fall-related physical injuries in a direct manner. It may include hip protectors, fall arresting harnesses and various other forms of protective devices. Hip protectors, for example, can provide direct protection against hip fracture injuries caused by the devastating impact force associated with many fall accidents (see the recent review by Parker, Gillespie, & Gillespie, 2003).

Existing direct injury-prevention approaches also have substantial limitations that hinder their application and effectiveness at the population level. Wearing protective devices, like hip protectors, may induce a false feeling of 'absolute' safety and thus promote dangerous behaviors, thereby increasing the possibilities of falls (Bloem, Steijns, & Smits-Engelsman, 2003). The more critical issue is user compliance. For example, after an initially high acceptance rate of the hip protectors, it was found that up to 75% of participants wore the hip protector inconsistently, and up to 50% refused to wear them altogether (Kannus, et al., 2000). These limitations associated with direct protection systems warrant research on other forms of protection systems with less discomfort and higher user compliance.

Given the limitations associated with existing fall-prevention and injury-prevention strategies, an indirect injury-prevention approach (i.e. fall event detection) is warranted. Automatic fall event detection, contrary to direct injury-prevention approaches, may reduce the fall-related injuries in an indirect manner. The idea of fall event detection is to detect the occurrence of an impending fall event through human motion characteristics prior to falling (Nyan, Tay, Tan, & Seah, 2006), during impact (Karantonis, Narayanan, Mathie, Lovell, & Celler, 2006) or post impact (Williams, Doughty, Cameron, & Bradley, 1998). Conventionally, fall event detection is beneficial to ensure the timely arrival of remote medical assistance without or with minimal human intervention, thereby reducing injury-related complications and mortalities. Timely medical attention is especially meaningful for those elderly who live alone. More importantly, fall event detection during the period prior to the fall impact (Nyan, Tay, Tan, et al., 2006) may pave the road for on-demand (active) fall injury prevention systems (e.g. active air bags) (Wu, 2000), thereby directly prevent the physical injury associated with fall accidents.

Promising as it may seem, fall injury-prevention solutions via event detection face two major problems. The first problem is concerned with detection performance, more specifically the balance between misdetection and a false alarm. Due to the heterogeneity of between-subject motion features and ambiguity of within-subject activity characteristics, higher fall detection sensitivity is always found to be associated with higher false alarm rates (Noury, et al., 2003). Almost all of the current fall detection techniques are facing this issue to a varying degree. The second major problem is that the target of detection is unclear. Different devices may actually detect the impact of a fall, the incapacity to rise/recover after a fall (post the fall impact), or the fall itself (the postural disturbance prior to the fall impact). From the perspective of preventing fall injuries directly using an on-demand protection system, timely and accurate detection of a fall event prior to an impact is of most relevance. Unfortunately, very few studies have been conducted in this area (Karantonis, et al., 2006; Lindemann, Hock, Stuber, Keck, & Becker, 2005; Nyan, Tay, Seah, & Sitoh, 2006).

In summary, existing fall-prevention and injury-prevention strategies are far from effective. Indirect injury-prevention approaches like fall event detection appear promising but are still problematic. This current study addressed these problems by developing a wearable, automatic fall event detection technology utilizing cost effective MEMS based accelerometers and gyroscopes that provide motion data to capture a fall event.

1.1.2. The current study on fall event detection

As stated above, existing fall event detection research is mainly suffering from the balance issue between misdetection and false alarm. This current study intended to solve this problem by developing a new fall detection algorithm and a new integrative ambulatory measurement (IAM) framework.

The performance problem can be remedied by a new fall detection algorithm. The issue with misdetection and false alarm arises from "information ambiguity" between simple motion features generated during falling and those generated during activities of daily living (ADL). The basic idea behind fall detection through motion features is that common ADLs are usually executed in a controlled manner, while unusual abrupt motions such as falls do not (Lindemann, et al., 2005; Nyan, Tay, Tan, et al., 2006). Such a characteristic is especially true for the elderly who are in a great need of fall protection. Previous fall detection algorithms typically employ only one dimensional motion intensity information, such as the vertical acceleration, orientation, and angular rate. In contrast, the new algorithm in the current study intended to use two-dimensional information of angular kinematics (i.e. angle and angular rate) to detect backward falling. It is argued that abrupt motion intensity (backward angular velocity) together with unusual body orientation (backward lean) will better distinguish fall accidents from common ADLs. Technical details about this algorithm are presented in Chapter 3.

Detection performance is also largely influenced by individual differences. One way to solve this problem is to apply individual calibration and to adopt individual-specific fall detection threshold criteria. Theoretically, the individual calibration approach is attractive as it offers a more precise detection threshold tailored for each individual, thereby potentially achieving an optimal balance between misdetection and false alarm. However, practical constraints limit the wide application of current individual calibration procedures. Currently, these procedures require dedicated facilities and trained personnel, take longer to implement, and certainly are not cost-effective. Additionally, it is unknown to what extent the individual-specific threshold determined in the laboratory represents the true, optimal threshold of that individual in a real life situation. Therefore, an alternative approach that is capable of providing in-the-field automatic calibrations must be sought.

Currently, the ambulatory measurement approaches are either non-real-time, in which the data measurement is separated from data processing, or real-time, in which the data analysis is performed simultaneously with the data capturing. The non-real-time approach is most widely used as it is not limited by the available processing time. Thus, there are no constraints on the complexity of the analytical algorithms that can be implemented. More importantly, since all of the data is available at the time of processing, the current motion status can be determined using the information about the future events. Compared to the non-real-time approach, the real-time approach is superior in terms of fast response and is the only option for applications like fall event detection.

Detection performance negatively influenced by individual differences can benefit from the integrative ambulatory measurement (IAM) framework in the current study. The idea of this framework is to combine both non-real-time and real-time data processing components, to share information between components and to handle ADL classifications and fall event detections in non-real-time and real-time components, respectively. The ADL information obtained in the living environment can be used to update the fall detection threshold adopted in the real-time component. In other words, individual calibrations can be done automatically using this framework. Technical details about this framework will be shown in Chapter 3.

1.2. Objectives and Hypotheses

The focus of the current study was on the theoretical construction of a new fall event detection algorithm and a new integrative ambulatory measurement (IAM) framework which could further enhance fall detection performance. Laboratory experiments were conducted to evaluate the performance of the new algorithm in differentiating a slip-induced backward fall from ADLs. As shown at the beginning of the Rationale section, slip-induced falls represent a significant portion of fall-related injuries. Therefore, the current study limited its scope to slip-induced backward fall. Once proved effective, the research paradigm used in the current study can be easily extended to other types of falls in future research. The underlying assumptions for the current study were that (1) there exist certain motion features that are unique to fall activity and these motion features can be used to differentiate falls from ADLs effectively, and (2) the ambulatory sensors can adequately measure these unique motion features associated with falls. These assumptions, whether explicit or implicit, are present in most relevant experimental literatures.

The current study had the following two specific aims and two primary hypotheses:

Specific aim 1: Develop a new fall event detection algorithm and evaluate the performance of the new algorithm in detecting a slip-induced backward fall from other common ADLs (i.e. sitting down, lying down, bending over, etc.).

Specific aim 2: Develop a new ambulatory measurement framework integrating both real-time and non-real-time components. Evaluate the utility of the individual calibration function provided by the IAM framework in enhancing the fall detection performance of the new algorithm.

Hypothesis 1: Backward fall motion characteristics as measured by peak sagittal trunk angle and angular velocity would be significantly different from common ADLs' trunk motion characteristics.

Hypothesis 2: Fall detection performances of the new algorithm utilizing both a gyroscope and an accelerometer and with an individual calibration, as measured by sensitivity, specificity and response time, would be significantly better than the existing algorithm (Nyan, Tay, Tan, et al., 2006) utilizing a gyroscope only and without calibration.

Corresponding to the above specific aims and hypotheses, two studies were performed. Study 1 involved a biomechanical analysis of trunk motion features during common ADLs and slip-induced falls using an optical motion analysis system. This study was intended to facilitate the development of the new fall detection algorithm (specific aim 1) and the individual calibration function from the IAM framework (specific aim 2) and to evaluate the first primary hypothesis. Study 2 involved collecting laboratory data of backward falls and common ADLs using ambulatory sensors. This study was designed to answer whether the new algorithm would be superior to the existing algorithm, and whether the individual calibration function provided by the IAM framework would further enhance the performance of the new algorithm (hypothesis 2).

1.3. Expected contributions

The current study aimed to reduce the fall-related injuries by detecting fall events utilizing ambulatory measurement technology. This study was expected to have the following contributions:

First, by detecting the occurrence of fall accidents, it is possible to ensure the timely arrival of the medical assistance from remote locations. This is particularly beneficial for frail elderly who live alone (i.e., rural settings). Together with the support from emergency response facilities, accurate fall event detection could prevent and minimize the injuries incurred during the waiting period after a falling episode. Compared with the existing fall detection approaches, the new method has the advantage of being able to actively update its detection threshold, thereby increasing its detection performance.

Second, ambulatory detection of fall accidents can serve as an attractive research tool in fall epidemiological studies. Currently there are no accepted methods for reporting falls, and there is limited data on the reliability and validity of the different reporting systems. The current study is expected to facilitate the accurate and objective documentation of fall accidents.

Third, successful detection of fall events with sufficient accuracy and fast response would also lead to the further development of automatic and on-demand PPE which may directly reduce and prevent the physical injuries incurred during the impact phase of fall accidents.

The current study also contributed to the ambulatory measurement research by offering a new human activity classification framework (IAM framework). Even though the development of this framework was primarily motivated by a fall event detection scenario, this framework could be utilized in a variety of applications including long-term tracking and monitoring of the risk of falling or changes in the risk of falling due to aging or pathological conditions.

Chapter 2

2. LITERATURE REVIEW

This literature review will start with the epidemiology of fall accidents, followed by the current developments and limitations of fall event detection research. As ambulatory measurement technology is the ground for the ambulatory fall detection, various types of ambulatory sensors and their applications in different biomechanical scenarios will also be reviewed.

2.1. Fall epidemiology

2.1.1. Consequences of fall accidents

Physical injuries are the most important and obvious consequences of fall accidents. Among all of the fall-related injuries, hip fracture is particularly common and devastating. Most hip fractures are caused by a direct impact on the trochanteric area of the hip (Nevitt, et al., 1993). Approximately one fourth of the fall accidents result in hip fracture (Lauritzen, Petersen, & Lund, 1993). The severity of a hip fracture is determined by three factors: the impact energy created by the fall, the energy-absorption capacity of the soft tissue surrounding the hip joint, and the bone mineral density property (Parkkari, Heikkila, & Kannus, 1998). Upper extremity injuries are also common physical injuries of falls. In case of unrecoverable fall accidents, use of the upper extremities to protect the head and trunk from impact is a common fall-arrest strategy (Hsiao & Robinovitch, 1998). However, this strategy may result in substantial arm and wrist fractures. It has been shown that for 79% of those aged more than 50, distal forearm fractures were resulted from falls (Oskam, Kingma, & Klasen, 1998).

Besides direct physical injuries sustained during the fall impact, there is an indirect injury effect of fall accidents caused by lack of timely medical assistance. For those elderly living alone, a common phenomenon after falling is the so-called 'long-lie'. 'Long-lie' is defined as involuntarily lying on the ground for an hour or longer after falling (Lord, Sherrington, & Menz, 2001). Research has shown that the 'long-lie' occurs in more than 20% of the elderly hospitalized due to a fall (B. Vellas, Cayla, Bocquet, Depemille, & Albarede, 1987). Moreover, half of the elderly who experience a 'long-lie' die within six months, regardless of the occurrence of physical injury (Wild, Nayak, & Isaacs, 1981).

In addition to physical injury, fall accidents can also have psychological and social consequences in various aspects. First, elderly fall victims may lose independence. Studies have revealed that recurrent falls are a common reason for admission of previously independent elderly to long-term care facilities (Donald & Bulpitt, 1999; Grisso, Schwarz, Wolfson, Polansky, & Lapann, 1992). Second, falls lead to a fear of falling. Fear of falling and other post-fall anxiety syndrome are well recognized as important threats to the physical and mental well being of the elderly for reasons like association with depression, loss of social contacts, reduced dynamic stability due to stiffening, etc (Bloem, et al., 2003). Approximately one third of the elderly developed a fear of falling after a fall accident (B. J. Vellas, Wayne, Romero, Baumgartner, & Garry, 1997). The psychological trauma or fear of falling itself may also lead to reduction in physical activity beyond that due directly to physical injuries (J. C. T. Close, 2001). Additionally, fall victims may lose self-confidence to engage in normal daily activities, which result in self-imposed functional degradations (Brown, 1999; Clark, Lord, & Webster, 1993).

2.1.2. Causes of fall accidents

The mechanism of a fall can be described in various ways according to different researchers. For example, Leclercq (1999) proposed that a fall is composed of imbalance (e.g. slips, trips, etc), attempt at equilibrium recovery and in the event of failure, fall with eventual injuries. Lockhart et al. (2005) divided the inadvertent slip and fall process into four distinct phases: environment, initiation, detection, and recovery. Common to all these descriptions, there are both intrinsic and extrinsic factors that contribute to the fall accidents.

There are potentially over 400 factors contributing to the risk of falling (Masud & Morris, 2001). From a broad sense, they can be roughly classified into intrinsic and extrinsic causes. The intrinsic factors involve aging, attention, physical status, fatigue, etc. The extrinsic factors are mainly environmental (floor surface, shoes, lighting, etc). From the perspective of biomechanics and ergonomics, intrinsic factors can be considered either as permanent/non-modifiable, such as prevailing characteristics of balance recovery strategy and predisposing psychological or physiological factors, or as momentary/modifiable, such as fatigue, attention, medication. Epidemiologically, the most likely cause of fall accidents was identified as accident/environment-related, followed by gait/balance disorders or weakness (Kenny, 1996).

Risk factors of falling can also be classified in other ways. Aiming at the multidisciplinary effort towards fall prevention, Close (2001) identified four categories of fall risk factors: general, physiological/functional, medical risk factors, and medication. From a general health care perspective, the Effective Health Care Bulletin (EHCB) classified the causes of falling into five major categories:

environmental, medication, medical conditions and changes associated with aging, nutritional, and lack of exercise (Oakley, et al., 1996). Particularly concerned with occupational settings, Gauchard et al. (2001) suggested incorporating the organizational factors (inadequate signs and indicators, inadequate maintenance schedules, etc) into extrinsic factors to reduce the fall accidents associated with workers. Despite the various classifications of risk factors of falling, it is important to realize that fall risk is a continuum, which varies continuously with the changing environment and individual intrinsic status (e.g. age, health status, etc) (Harwood, 2001).

2.2. Fall event detection

Fall event detections started from the early community dispersed alarm system. The fall-prone elderly, especially who live alone, are provided with push-button radio-based emergency pendants which can open a telephone channel to a response center (Williams, et al., 1998). However, in the event of a devastating fall, the ability of the victim to activate such an alarm system is often compromised: they may not have the required intelligence or the mobility to do so. This situation calls for the development of automatic fall detectors requiring minimal human intervention in case of emergency.

2.2.1. Current developments

As early as in 1991, Ellis et al. (1991) filed a patent for a personnel man-down alarm system. The proposed system essentially detected a fall as personnel inactivity for a predetermined period of time. Such a methodology belongs to the category of post-fall mobility detection (Figure 1). A foreseeable problem with this system is that activities like lying down may be mis-detected as a fall as well.

In the research domain, Williams et al. (1998) developed a smart fall and activity monitor to be integrated into a telecare system (which is an intelligent health status monitoring system). The so-called fall events, which can be recovered, and fall-alarm, which resulted in the dangerous inactivity, were detected by a fall impact sensor and threshold method. Fall impact threshold was individually tuned to compensate for individual's weight and height. Body orientation of the individual was detected to aid more accurate fall detection. However, the details about the sensor construction and the detection algorithm were not disclosed. In addition, the performance of the proposed system was not assessed.

Two year later, Doughty et al. (2000) suggested a set of comprehensive requirements for fall detection device design from the clinical perspective. Particularly, it was emphasized that an acceptable fall detector must be designed in such a way that it does not label the wearer as a person who lacks independence, which would adversely affect user compliance. As an initial practice for these requirements, the authors proposed a two-stage fall detection solution, which in essence involved a lying or reclining detection stage and impact detection stage. The proposed method was tested on five different types of falls using a mannequin. By performing this test on various sites of the mannequin, it was concluded that wrist was not suitable for mounting a fall detection sensor. Unfortunately, details of the fall detection algorithm were not disclosed.

About the same time, Noury et al. (2000) developed the first accelerometer-based smart fall sensor. The so-called 'Actimeter' was composed of a uni-axial accelerometer, a position tilt switch, and a mechanical vibration detector. This sensor pack provided information about the vertical acceleration shock, the body orientation, and the mechanical vibration of the body surface. Using the threshold technique, the fall event was detected from normal daily activities. The performance of this sensor, however, has not been evaluated.

Similar to the idea of detecting post-fall inactivity (Ellis, et al., 1991), Peterlenz et al. (2002) filed a patent which detected the fall whenever the body angle was at a steady state for a period of time (i.e. 2 s). As a refinement, their algorithm also confirmed the fall detection by comparing the motion intensity (i.e., acceleration) against a certain level of thresholds.

Later, Noury et al. (2003) developed another accelerometer-based fall sensor to differentiate fall events from normal daily activities. The fall sensor was composed of a bi-axial accelerometer only and was placed on a belt under the participant's armpit. Ten young participants were involved in laboratory testing. Eleven types of fall scenarios including fall recovery and syncope (temporary loss of consciousness), and four types of normal daily activity were evaluated. The proposed method, though not clearly described, achieved a specificity of 83% and a sensitivity of 79% overall. In addition, the results clearly indicated that higher fall detection sensitivity was always associated with higher false alarm rates.

To increase the ease of use, Degen et al. (2003) presented a fall detector in the form of a wrist watch. Resultant acceleration was measured by the embedded tri-axial accelerometer. The idea was to detect a potentially harmful downward velocity, which was indirectly measured by integrating the resultant acceleration. Simulated falls were tested using one subject and overall successful detection rate was 65%, which was considered too low to be of any practical value.

In the patent domain, Lehrman et al. (2004) developed another activity monitoring system which was also capable of detecting a fall. A unique feature of this system, as it claimed, was that it was capable of determining whether the detector was connected to a body during the fall or whether only the sensor experienced the fall. Such feature is very meaningful in practical implementation because the situation when the sensor was detached from the body may represent an important source of false-alarms in fall event detection.

The latest fall detection patent was filed in 2005 (Clifford, Borras, & Gomez, 2007). It was claimed that a fall can be detected by comparing the body acceleration to a value range. The proposed system and method can further detect the inactivity of the wearer subsequent to the fall event. However, the detection algorithm and the performance evaluation were not disclosed in details.

Automatic fall event detection does not have to be confined to body-fixed ambulatory sensors. For example, Nait-Charif et al. (2004) presented an interesting video-based fall detection solution. The rationale was that inactivity outside the usual zones of inactivity (e.g. chair, bed) is likely to be a cue for a dangerous fall event. An algorithm was proposed to process the video image from a home based surveillance camera to determine the location of the inactivity. However, the performance of the proposed method was not assessed.

A similar video-based fall detection solution was also proposed by Chia-Wen et al. (2005). The authors proposed a vision-based compressed-domain fall detection approach. An intelligent video surveillance system was adopted to automatically detect an unusual events like fall accidents. One advantage of this method, compared to the one developed by Nait-Charif et al. (2004), was that it could utilize the entire network of surveillance cameras and did not limit its application to the home environment. Unfortunately, this approach was not empirically evaluated, neither.

With the advancement of MEMS technology, ambulatory sensors like accelerometers and gyroscopes can be made in a more portable form, which further promotes the development of accelerometer-based fall detection sensors. Recently, Hwang et al. (2004) developed a real-time, wireless fall detection system. The proposed fall sensor was composed of a tri-axial accelerometer, a gyroscope, a tilt sensor, and a Bluetooth module. It was attached onto the individual's chest. Three young participants were instructed to perform three types of falls as well as normal daily activities. The fall detection was achieved using threshold technique. The results indicated an accuracy of 96.7%, with a few side falls failing to be detected. Despite such excellent detection rate, this algorithm does not provide the convincing results on the rate of false alarm, which is another must-have performance measure of any practical fall detector.

At approximately the same time, Diaz et al. (2004) presented a falling monitor within the framework of a telecare system. An accelerometer pack with four sensitive axes was designed in the form of a skin patch to be attached on the upper back. Threshold technique involving both the acceleration threshold (1.4g) and the energy threshold was used to detect the fall events. Eight young participants were involved in a laboratory testing with simulated falls and normal daily activities. The authors witnessed the strong influence of the subject in the performance of the algorithm. Meanwhile, it was found that as the accuracy of the true falling events detection increased, the rate of false alarm increased as well.

While fall detection sensors have been developed with the objective to reduce physical injuries associated with the actual fall accidents, these sensors may also have a social impact. Brownsell and Hawley (2004) investigated whether wearing automatic fall detectors would reduce the fear of falling among community users. It turned out that most users who wore the detectors at least occasionally, felt more confident and independent, compared to the control group. This finding provided the evidence that wearing a fall detection sensor can promote the quality of life from the social perspective.

One problem with the fall sensor design so far is the difficulty to filter out the rigorous activities with features similar to falls. One possible solution is to carefully select a suitable site of attachment. For example, Lindemann et al. (2005) placed their fall detection device behind the ear. It was hypothesized that the individual would try to protect the head from high accelerations and thus the high accelerations measured at the head level must be associated with unpleasant or unintentional movements such as falls. One tri-axial accelerometer was integrated into a hearing aid housing that was fixed behind the ear. The sensitivity of the fall detection algorithm was evaluated on one young participant during intentional falls. Seven fall scenarios and five types of daily activities were tested.

The fall detection algorithm involved three universal trigger thresholds based on accelerometer signals. Very high sensitivity and specificity levels were achieved.

Choice of sensor site is also of great importance to enhance user compliance. More recently, Nyan et al. (2006) proposed a wearable daily activity monitor system, with the capability to detect falls. Interestingly, a tri-axial accelerometer was embedded into a garment, and attached close to the shoulder. The authors proposed a threshold (4.8g) based fall event detection algorithm, though the performance of this algorithm was not tested in this study.

Karantonis et al. (2006) presented another implementation of a real-time activity monitor system with fall detection capability. A tri-axial accelerometer was worn on the participant's belt, close to the right ASIS of the pelvis. The measured signals were wirelessly transmitted to a local computer via the ZigBee network. The daily activity classification algorithm was based on the framework proposed by Mathie et al. (2004). The major improvement of this system was to perform the vast majority of the signal processing onboard using the embedded intelligence. A possible fall was detected whenever there were two consecutive peaks of the resultant acceleration over a fixed threshold (1.8g). The detected possible fall was further verified as a real fall by detecting the inactivity for a period of time after the possible fall. Six healthy young individuals were instructed to perform activities with a standard protocol, including the simulated falls. An excellent successful fall detection rate (which means less misdetection) was found, though the false alarm rate was not clearly described. The authors also acknowledged the difficulties to distinguish between fall and sitting or lying down vigorously.

Up to now, the fall detection sensors have been composed of either the accelerometer alone or the combination of accelerometers and other sensors. Recently, researchers also attempted to develop non-accelerometer-based fall sensors. For example, Nyan et al. (2006) explored the feasibility to distinguish sideway and backward falls from normal daily activities using gyroscopes alone. Three gyroscopes, embedded into a smart shirt, were approximately positioned at sternum, front waist, and right underarm, respectively. Ten healthy young participants were instructed to follow a standard activity protocol. A pneumatically actuated fall simulator was employed to induce sideway and backward falls to the participants. Fall incidence was identified whenever the gyroscope signal exceeded a certain threshold, which were established through the normal daily activities. The results indicated that all the falls were successfully detected (sensitivity = 100%), though several false alarms were also found (specificity ranged from 92.5% to 97.5%). Lead time was found to range from 98ms to 220ms. This study is significant as it represented the first approach of its kind to detect fall accidents prior to impact and to evaluate the lead time, which might be useful in activating fall impact reduction system.

The latest fall detection research was reported by Bourke et al. (2007a). A threshold-based algorithm capable of detecting fall events using accelerometers was described. Two tri-axial accelerometers were placed on the trunk and thigh, respectively. Ten young adults performed eight different types of simulated falls, including forward, backward, lateral to the left and lateral to the right fall, all performed with both legs straight and with knee flexion. In order to increase the robustness of the proposed methodology, ten elderly individuals performed a series of normal activities which can potentially produce a false alarm. The designed daily activity protocol included different types of sitting down and standing up, getting in and out of a car, and walking. Two types of fall threshold were empirically determined for both trunk and thigh sensors. Trunk upper fall threshold (3.52g) was found to produce excellent detection accuracy without any false alarms, which concluded that the trunk was the optimum sensor placement site for fall detection.

2.2.2. Limitations with current research

The most serious limitation in current fall detection research is its efficacy, or more specifically the balance between the misdetection and false alarm. Due to the time critical nature of fall event detection, the threshold techniques are adopted unanimously. Different algorithms may use one or various combinations of a few motion features including velocity, acceleration, angular kinematics, and orientation as the fall detection criteria. For most algorithms, the detection threshold is same universally for all the participants under study. Due to the fact that different individuals may have different motion patterns and characteristics, the fall threshold criteria that are appropriate for one individual may not be suitable for another individual. A higher threshold would result in fewer false alarms but more misdetection. On the contrary, a lower threshold would result in less misdetection but more false alarms. As one may expect, the more heterogeneous the users are, the less balanced the detection performance will be. Almost all the current fall detection techniques are facing this dilemma. A recent accelerometer-based fall detection study clearly showed that higher fall detection sensitivity was always associated with higher false alarm rate (Noury, et al., 2003).

The negative influences of such performance issues are obvious. A high rate of false alarms may cause emergency respondents to ignore the subsequent alerts, and the user to temporarily remove or even completely reject the device. On the other hand, a single misdetection (missed true emergency) may lead to a loss of confidence in the system and promote the loss of the independence which the fall event detection technology is supposed to prevent. This false alarm problem is also the main reason that various fall detectors have become available in the research domain for a couple years, but have failed to become accepted by the end users and to show benefits towards fall accidents in practice.

Another efficacy issue is concerned with the external validity. More specifically, to what extent the experimental results obtained from the lab studies and the simulated fall protocols can be generalized to the general population and generic fall accidents? For safety and ethical considerations, the laboratory studies often involve healthy young participants, as opposed to the frail elderly by who such fall detection systems are intended to be used. The movement characteristics between these two groups are expected to be different. Although these studies are sufficient from a technical validation perspective, the obtained findings should to be generalized with caution. In addition, the falls in the lab studies are often simulated, though the actual protocol has evolved over time. Scientists have studied the falling of mannequins (Doughty, et al., 2000), voluntarily falling (Bourke, et al., 2007a) and unexpected falling (Nyan, Tay, Tan, et al., 2006) of human participants from a standing posture. Because most fall accidents occurred while the victims are in motion, researchers have to be aware of the differences between the simulated falls in the laboratory studies and the fall accidents in real life. In addition, the environmental circumstances in a laboratory setting as used by most fall detection studies are artificial, thereby their resemblance to real-life environments can be questioned (Kiani, Snijders, & Gelsema, 1998).

Besides the efficacy, the applicability of fall detection is also of importance. To achieve sufficient user compliance, the fall detectors should be designed in a way that it will not reveal the user as being frail or dependent (Doughty, et al., 2000). The location and the number of the sensors have to be considered to minimize user discomfort, thereby maximizing the user compliance.

From a research perspective, sometimes the target of the detection is unclear. Different studies may actually detect the impact of a fall, the incapacity to rise/recover after a fall, or the fall itself (the postural disturbance). Often, the effectiveness of the proposed fall detection method was either not validated (Nyan, Francis, et al., 2006) or not described sufficiently (Doughty, et al., 2000). Even the analytical algorithm was not explained in some cases (Doughty, et al., 2000; Noury, et al., 2003). All of these will greatly hinder the comparison and further development of fall detection research.

2.3. Ambulatory sensors

There are a range of ambulatory sensors that are commonly used in biomechanics applications. They include accelerometers, gyroscopes, magnetometers, pedometers, force sensitive resistors, goniometers, tilt sensors, and pressure sensors. This section will review different types of ambulatory sensors in terms of the working mechanism, the output parameters, and the advantages and disadvantages in relation to human biomechanical research.

Compared to the conventional motion capture systems (i.e. optical-, magnetic-, and sonic-based systems) (Aminian & Najafi, 2004), ambulatory sensors have the general advantages of being portable, lightweight, and cost effective. They require very low power consumption and no dedicated measurement facility; thereby, they are extremely suitable for long-term monitoring in a daily living environment. Ambulatory measurements are conceptually not limited in measurement space and time. Taking the gait analysis scenario as an example, the optical motion capture system which is prevalently used in biomechanical research laboratories requires the participants to move inside a closed and restrained space, and is only able to measure a limited distance, containing a few gait cycles.

2.3.1. Accelerometer

Accelerometers are devices that measures the linear acceleration exerted on the device along one to three orthogonal axes (i.e. AP, ML and VT). They typically consist of a mass, connected to a frame by a beam which can be represented by the form of a damped spring. The acceleration experienced by the suspended mass is transformed to the spring deformation, which is then converted into the variable voltage output via various mechanisms. Depending on the type of sensor construction, the conversion mechanism can be either a change of electrical impedance (resistive or capacitive accelerometer) or charge generation (piezoelectric accelerometer) (Aminian & Najafi, 2004).

Piezoelectric accelerometers can only be used to measure dynamic motion, due to a phenomenon known as 'leakage' which specifies that the charge in the piezoelectric element dissipates in time (Chen & Bassett, 2005). This characteristic makes the piezoelectric accelerometers unsuitable for detecting human static posture. On the contrary, both resistive and capacitive accelerometers are sensitive to both static and dynamic accelerations. Because of this feature, they are capable of measuring gravity in the absence of movement and, therefore, are able to assess human static posture as well as dynamic activity.

Being able to detect static acceleration (gravity) can be a disadvantage for accelerometers. In most situations, the measurement of interest is the inertial acceleration induced by the body movements. However, both the inertial acceleration and the gravitational acceleration components are always superimposed. Since the change of segment orientation with respect to the vertical axis is unavoidable, the gravity influence is present as a component with variable magnitude in the accelerometer output. This characteristic makes the separation between inertial acceleration and gravitational acceleration not always simple and straightforward.

The utilization of accelerometers in ambulatory measurement has proven to be very promising in a variety of biomechanics applications (see sections 2.4~2.7 of this chapter).

2.3.2. Gyroscope

A gyroscope is a device measuring the angular velocity about its sensing axis. It usually consists of a vibrating element coupled to a sensing element, acting as a Coriolis sensor (Tong & Granat, 1999). The Coriolis Effect describes the apparent deflection of an object as a result of the Coriolis force. This Coriolis force is proportional to the angular rate of rotation. Therefore, the mechanical deformation of the internal object measured by the gyroscope corresponds to the angular velocity. For a piezoelectric gyroscope, the operating principle is to measure the Coriolis acceleration generated when a rotational velocity is applied to the oscillating piezoelectric bimorph (Aminian, Najafi, Bula, Leyvraz, & Robert, 2002).

Gyroscopes are small, lightweight, easy to use, and have a fast response, making them ideal for joint motion measurement and a popular choice in ambulatory measurement. Compared to other ambulatory sensors, especially accelerometers, gyroscopes have many advantages. First of all, the gyroscope is not as sensitive to attachment locations as the accelerometer. As shown by Tong et al. (1999), the gyroscope can be placed anywhere on a body segment as long as its sensing axis is parallel to the same rotation axis where the desired joint motion occurs, and the measured angular rotation will not change along that segment. Second, under the same testing condition, the angular velocity signal from gyroscopes are less sensitive to noise than the acceleration signal produced by the accelerometer (Aminian, et al., 2002). Third, there is no gravitational influence on the measured signal from gyroscopes. This is a very desirable feature of gyroscope, compared to accelerometers, especially in conditions where gravitational influence is difficult to eliminate.

There are also limitations associated with gyroscopes. One major issue with solid-state gyroscopes is the zero frequency offset, or bias, when the sensor is not in motion (Lee, Laprade, & Fung, 2003). This offset will result in an angular drift during the integration process of the gyroscope signal. In other words, orientation estimation using gyroscopes without any correction mechanism or algorithm is prone to integration drift (Luinge, Veltink, & Baten, 2007). Other than the drifting error, the gyroscope is also more expensive and more delicate to use than the accelerometer.

Many methods have been proposed to compensate for the drifting error. One common approach is to high-pass filter the signal (Miyazaki, 1997). Alternatively, this error can be minimized by advanced algorithms and/or the signals from other types of sensors (e.g. accelerometer). Luinge et al. (1999) suggested an approach to predict the drifting error and, thus, compensate for such an error using a Kalman filter and the accelerometer signal. Another type of approach is to utilize the expected characteristic(s) of the target signal. For example, in gait analysis applications, foot orientation can be expected during the stance phase. Based on this principle, Williamson et al. (2001) employed a mathematical technique to auto-null and auto-reset the gyroscopes in order to limit the propagation of the drifting error.

2.3.3. Magnetometer

Magnetometers are used to detect rotation with respect to the earth magnetic field based on the magneto-resistive effect. They can provide additional information about the orientation of the body segment to which it is attached. Magnetometers are usually used in a sensor pack to complement the signal from accelerometers or gyroscopes, especially in those kinematic sensors developed recently (Kemp, Janssen, & van der Kamp, 1998; Lee, et al., 2003).

One disadvantage of magnetometer is its sensitivity to nearby ferromagnetic metals and local magnetic fields as generated by electronic equipments (Luinge, et al., 2007). In addition, magnetometers need to be frequently calibrated to maintain accuracy (Aminian & Najafi, 2004).

2.3.4. Pedometer

Pedometers are mechanical movement counters that are designed to detect steps and further estimate walking distance and metabolic cost during walking. They can be clipped to the belt at the waist or worn at the ankle. There are typically three operating mechanisms of pedometers (Crouter, Schneider, Karabulut, & Bassett, 2003; Zheng, Black, & Harris, 2005). The first mechanism utilizes a spring-suspended horizontally leveled arm together with an electrical circuit. The electrical contact triggered by the level arm motion is detected as one step. In the second mechanism, the mechanical switch is triggered by changes in magnetic field. The construction of the third type of pedometer is similar to an accelerometer. The number of zero-crossings of the instantaneous acceleration is detected as steps.

Being simple, lightweight and very inexpensive, pedometers have been successfully applied in many occasions to assess the level of physical activities in real-life situations (Balogh, et al., 2004; Bassett, Cureton, & Ainsworth, 2000; Croteau, 2004; Steele, et al., 2003; Talbot, Gaines, Huynh, & Metter, 2003).

Despite wide application, pedometers suffer from being unable to provide information regarding the type or pattern of the activity, which may vary considerably between individuals (Zheng, et al., 2005). Even during walking, pedometers are inaccurate in estimating walking distance and energy expenditure. In a comparison study of 10 pedometers (Crouter, et al., 2003), it was found that the estimation error of pedometers for distance and energy expenditure were as high as 10% and 30%, respectively. The accuracy of pedometers further decreases at slower speeds, which limits its application in frail elderly with impaired gait functions.

2.3.5. Force sensitive resistor

Force-sensitive resistors (FSRs, also called pressure sensor, foot switch) are small flat resistors which measure applied force/pressure. An FSR is composed of two parts, with the first part being a film of resistive material and the second part being another film with a set of digitizing contacts (Aminian & Najafi, 2004). The operating principle of an FSR is the nonlinear changes in the property of resistance associated with the applied force/pressure. Due to the high material variation (up to 25% part to part repeatability, Pappas, Popovic, Keller, Dietz, & Morari, 2001), FSRs are not suitable for precise force measurement. Rather, they usually serve as two-state switches for monitoring temporal parameters in gait analysis.

The FSRs can provide satisfactory results in normal walking conditions. They also have been widely used as a criterion standard for gait events and phase detection (Aminian, et al., 2002). Skelly and Chizeck (2001) reported the real-time detection of gait events using force-sensitive resistors in

FES applications, and five different gait phases (foot-flat, heel-off, toe-off, max-knee-flexion, and heel-strike) were successfully distinguished.

However, FSRs also have limitations. Due to the nature of the measurement, they alone cannot distinguish different types of weight transfer (e.g. weight lifting from one leg to the other) from walking. The reliability of their application with pathological gait (e.g. shuffling gait) is limited (Mansfield & Lyons, 2003). Even with normal gait, FSRs are completely 'blind' with the swing phase. In terms of real-life scenarios, there is a user compliance issue. FSRs under the feet are generally not suitable as they require long cables to connect to a portable unit, which is usually worn at the waist (Veltink, Bussmann, de Vries, Martens, & Van Lummel, 1996). In addition, issues like mechanical failure may be more prominent in the daily living environment.

2.3.6. Goniometer

A goniometer is an electrical potentiometer that measures a joint angle across adjacent body segments. There are typically three types of goniometers, including the universal goniometer, fluid goniometer and electrogoniometer. The latter has been reported to have the lowest inter-session variability (Goodwin & Sunderland, 2003). In addition, it is generally not recommended to use different types of goniometers interchangeably (Zheng, et al., 2005). Due to the different physical sizes in different joints, goniometers can have different physical sizes, as they are anthropometric-dependent (Zheng, et al., 2005).

Goniometers have the advantages of being inexpensive and sufficiently accurate for gait analysis. In a comparison study (Shiratsu & Coury, 2003), most goniometers are found to able to produce an sufficiently accurate measurement (mean error < 5º) as accepted by American Medical Association for clinical use. Goniometers have been widely used to measure the range of motion (ROM) for wrist and forearm (Hansson, Balogh, Ohlsson, & Skerfving, 2004; McGorry, Chang, & Dempsey, 2004), knee (Kuiken, Amir, & Scheidt, 2004), back (Shiratsu & Coury, 2003), cervical spine and neck (Haynes & Edmondston, 2002).

At the same time, goniometers also have practical limitations that hinder their applications. A major source of error with the most popular electrogoniometers is cross-talk (Hansson, Balogh, Ohlsson, Rylander, & Skerfving, 1996), which is the incomplete decoupling of the measurement of motion in the two planes. For daily living scenarios, it is not always straightforward to determine the exact joint center of rotation and it is not always easy to attach the device by individuals, especially those frail elderly with functional limitations. Additional limitations include lack of robustness (vulnerable to breakage) and only being able to provide relative angular displacement information (Zheng, et al., 2005).

2.4. Ambulatory daily activity classification

2.4.1. Activity monitor

Monitoring of ADLs (activities of daily life) enabled by ambulatory measurements can be used to provide an objective indication of the activity levels or restrictions experienced by patients or elderly. A detailed assessment of ADLs offers a promising approach to objectively evaluate the effectiveness of experimental manipulations or medical interventions, such as rehabilitation programs, surgeries, medications, etc. (Bussmann, Tulen, van Herel, & Stam, 1998).

Back in 1995, Bussmann et al. (1995) performed an initial study to establish a starting point for ambulatory daily activity monitoring via accelerometers. Accelerometers were attached on the trunk and thigh segments. Simple analytical methods were employed to classify activities including lying, sitting, standing, walking, stair ascent and descent, and cycling.

One year later, Veltink et al. (1996) continued Bussmann's work and developed a four-accelerometer configuration (one bi-axial accelerometer on sternum, one uni-axial accelerometer on each thigh). Static posture and dynamic motion were determined by examining the signal variability of the thigh-mounted accelerometer. After discriminating between static and dynamic activities, the type of static motion (posture) can be determined by investigating the combination of thigh and trunk orientations. The author suggested that two uni-axial accelerometers (one on trunk and one on thigh) are sufficient to discriminate sitting, standing and lying on the back. With the information provided by an additional sensitive axis (aligning with the media-lateral direction) of the trunk acceleration, their algorithm can also detect lying on the side. Discrimination of the types of dynamic activity (walking, stair climbing, and cycling) was based on the signal morphology (mean, STD, cycle time) and the curve correlation between template activity and test activity of trunk accelerometer output. The authors also acknowledged several limitations of this study, which included: 1) lack of classification performance evaluation and optimal setting of detector parameters (filtering parameters and thresholds); 2) only unambiguous postures can be detected; and 3) gait cycles were detected by foot switch. However, as an initial study, this paper demonstrated the feasibility of utilizing accelerometers in ambulatory activity classification.

Based on the similar orientation combination approach (Veltink, et al., 1996), Walker et al (1997) attached a set of position sensing switches onto the chest and the thigh to classify postures into sitting, standing and lying. In addition, step counts during walking were identified by an accelerometer mounted to the skin directly over the chest.

Continued from the initial development (Bussmann, et al., 1995) and theoretical background (Veltink, et al., 1996) mentioned above, Bussmann et al. (1998) conducted a validation study in the context of a psychological settings, to assess the effects of benzodiazepines on subject mood and cardiovascular functioning, in relation to daily activities. A configuration involving four accelerometers, two on the chest and one on each thigh, was adopted to mainly focus on posture detection. Participants were involved into a spontaneous testing protocol, in which they were allowed to move freely in a living room, and a standardized protocol, in which they had to perform a sequence of 40 different forms of sitting, standing, lying and walking. Overall agreement was found to be 88% and 96% for different protocols. The authors admitted that the best way to distinguish different types of dynamic activities was still under investigation. The validity of simpler (reduced number) sensor configuration was also investigated. It was argued that a three-sensor configuration, with the accelerometer only attached to one thigh, had little effect on posture detection performance, but walking quality information (e.g. symmetry) was lost with this configuration.

In order to evaluate pain treatment effectiveness, Bussmann et al. (1998) applied their activity monitoring methodology (Bussmann, Tulen, et al., 1998) in failed back surgery (FBS) patients. The patients were allowed to perform selected activities in their own way at their own home. The same sensor configuration, data processing, and data analysis as demonstrated above (Bussmann, Tulen, et al., 1998) was adopted and satisfactory agreement were achieved. For this study, taking measurements in a more natural, realistic environment can be considered to be a big step forward to confirm the external validity of ambulatory activity monitoring.

Aiming to improve activity classification accuracy, Kiani et al. (1998) adopted a similar four-sensor configuration (Veltink, et al., 1996) and used an artificial neural network (ANN) technique to identify daily activities. Because each ADL class would show extremely large inter- and intra-individual variation in a noisy real-life environment, they believed that simple signal processing techniques (peak detection, filtering, smoothing, and etc.) could not achieve satisfactory performance and that ANNs may not be a possible solution. Specifically, probabilistic neural network (PNN) with three phases (training, adjusting, and evaluating) was adopted for each individual in this study. The authors reported an overall agreement of 95%, though how the agreement was calculated was not clearly described. Errors were found to be mainly caused from the activities with short duration and the untrained activity samples.

In 1999, Foerster et al. (1999) explored the capability of their activity classification methodology (Fahrenberg, Foerster, Smeja, & Muller, 1997) in a realistic living environment. Participants were allowed to perform suggested activities in several places (coffee shop, library, etc) accompanied by an observer. Measurements from four accelerometers (located on sternum, wrist, thigh and shank) were compared with the activity profiles constructed during lab testing. Standardized L1 distance was adopted as the similarity measure. Though good classification results were achieved, this approach was limited by: 1) the performed activity had to be manually divided into segments; 2) the duration of each activity had to be longer than 20s; and 3) detection of postural transition was not involved.

In 2000, Tulen et al. (2000) applied the previously developed activity monitoring methodology (Bussmann, Tulen, et al., 1998; Bussmann, van de Laar, et al., 1998) to quantify the influence of a migraine attack on normal daily activities in the patients' living environment. Filtering techniques together with an instantaneous frequency analysis method was used to classify postures and activities and to estimate motility level (i.e. motion intensity) at three phases (before, during and after migraine attack). This study demonstrated the utility of ambulatory measurement in monitoring illness-related behavior change.

At about the same time, Sekine et al. (2000) attempted to classify acceleration signals during level walking and stair climbing in continuous records using time-frequency analysis of wavelet transform. Using direct wavelet transform (DWT) and wavelet packets, the low frequency components in AP (anterior-posterior) and VT (vertical) directions were reconstructed from a waist-attached tri-axial accelerometer and were used to detect the time of the change in walking pattern. The walking pattern within the detected period was then classified by the high frequency power in AP and VT direction. An overall classification rate of 98.8% was achieved. The authors claimed that this approach were superior to ANN, FFT and other ordinary filtering techniques, though the detection threshold of the change in walking pattern had to be empirically determined for each individual.

Later, Bussmann et al. (2001) reviewed their work in developing the ambulatory measurement and provided a comprehensive description of their ambulatory measurement technology. The algorithms in posture and motion detection were described in details. The classification accuracy was generally high except for stair climbing (sensitivity scores were 24%, 76%, and 49% in three studies), owing to the misdetection of walking. Some common methodological concerns including the participant's reactivity effect (Fahrenberg, et al., 1997) were discussed. Compared to the individual reference pattern approaches (Fahrenberg, et al., 1997; Foerster, et al., 1999), the authors claimed that the fixed threshold technique they adopted had the advantage of being transparent in its algorithm and requiring no initial reference recording.

Despite the popularity of using accelerometers and gyroscopes, attempts have also been made to explore the potential of other sensors or sensor combinations in the ambulatory measurement field. Morlock et al. (2001) developed a system using inclination sensors and goniometers to monitor daily activities for total hip arthroplasty (THA) patients. Two inclination sensors were attached on the thigh and shank, with one electro-goniometer attached across the knee joint. Three postures (standing, lying and sitting) were identified by testing whether the inclinations of thigh and shank were within the pre-determined ranges for a period of time. Differentiation between walking and stair climbing was achieved using information about max knee flexion angle and individual reference patterns. Frequency and duration of each posture/activity, as well as the number of steps during walking were determined in this study, though the validation procedure was not applied to all the patients.

Recently, Zhang et al. (2003) reported a new microcomputer-based portable physical activity measurement device (IDEEA). Tests were conducted for the identification of posture, gait, leg movements, and postural transitions (totally 32 types of physical activity). Five sensors (unknown type) were placed on the chest, thighs and feet. A protocol with a fixed duration (10s) for each activity was evaluated. A good identification rate (overall 98.7%) was achieved. Compared to previous literature, this study was able to identify a wide variety of postures and activities (such as leg movement at a certain posture). However, the classification algorithm was not described.

It has been a common belief that attaching sensors at multiple sites is required for accurate and reliable activity classification. Presently, sensors at multiple attachment sites have to be connected with cables or wires. One inherent problem with this approach is that they are cumbersome and interfere with ADL performance. Sensor configuration with only one attachment site would be ideal. In response to this issue, Najafi et al. (2003) tested the performance of a new system based on only one kinematic sensor attached on chest, in classifying activities of elderly individuals. The kinematic sensor was composed of two uni-axial accelerometers and one gyroscope. The sensor measurements, together with DWT algorithm and the explicit decision rules, was used to classify sitting, lying, standing, walking, and the associated postural transitions. As a unique feature, this study first detected and classified postural transition and then distinguished different postures adjacent to the detected postural transition. The accelerometer signals were only analyzed during the postural transitions. It was argued that, by dramatically reducing the required amount of computation, the proposed approach had the potential to be applied in real-time information processing.

Mathie et al. (2003) also employed a single accelerometer to detect daily activities. One tri-axial accelerometer was attached on the waist, above the right ASIS. Twenty-six healthy young individuals were instructed to perform a sequence of normal activities with fixed duration. The measurements took place in a controlled laboratory environment. Integrated acceleration signal within a window size were compared with a pre-set threshold. Although a standard protocol composed of a sequence of different activities was used, only two states, activity and rest, were discriminated in this study. Optimal detection parameters (filter length, window size and activity threshold) were also investigated.

Compared to the activities associated with the lower extremity and the trunk, studies investigating upper limb activities are limited. Schasfoort et al. (2003) developed an upper limb activity monitor (ULAM), which was used to determine the long-term impact of complex regional pain syndrome type I (CRPS1) in one of the upper limbs during everyday life. Daily activities were detected using their previous sensor configuration and analytical approach (Bussmann, et al., 2001). Two additional accelerometers were attached on forearm to produce a mobility feature. Variability in the acceleration signal of the forearm was regarded as the indicator of the upper limb mobility. A pre-set threshold was used to determine whether the upper limb was active. A clear impact of CRPS1 on upper limb activity was found, though the impact on general mobility (daily activity level) was modest.

Though the ambulatory systems have been demonstrated to be useful in both gait analysis and activity monitor areas, few studies have combined both applications together. Paraschiv-Ionescu et al. (2004) proposed an ambulatory system allowing the detection and assessment of both posture and the gait. Three kinematic sensors were placed on the chest, thigh and shank. The sensor on the chest was composed of a bi-axial accelerometer and a gyroscope. The sensor on the thigh was composed of a uni-axial accelerometer and a gyroscope. And the sensor on the shank was a gyroscope only. Three different methods in classifying postures (standing, sitting, lying and walking) were evaluated using signals or combinations of signals from accelerometers on chest and thigh, and the chest gyroscope. Walking detection was achieved by two methods based on the signals from shank gyroscope or chest accelerometer. Spatio-temporal gait parameters (swing and stance time, walking speed, cadence, stride length, joint angle and walking distance) were computed using the same double-segment model as reported before (Aminian, et al., 2002). Compared with other existing activity classification algorithms or systems, this system had the advantage of being more sensitive and accurate (98%~99%). One apparent limitation was the need for multiple fixation sites (including the shank).

In 2004, Mathie et al. (2004) conducted a pilot study to assess the feasibility of using an accelerometer system for unsupervised monitoring of daily activities in the home over extended periods. A tri-axial accelerometer was attached on the belt to the side of the body and connected with the computer wirelessly. Participants were trained to operate the systems and were asked to follow a standard calibration activity routine daily. Various features were extracted from each movement hourly and daily for each participant, and were tested for correlations with self-reported health status. Good user compliance was shown but training and support from the experimenter were needed for about two weeks to get the participants accustomed to all the procedures and operations.

As one can see, the above studies so far have provided substantial support for the feasibility of using accelerometers to identify postures and activities. However, each group developed its own algorithm and custom-made ambulatory system to tackle a specific set of movements. As indicated by Mathie et al. (2004), this poses two problems. First, the highly specific system and algorithm made it difficult to compare the results from different groups; second, it is difficult to adapt a specific algorithm to a different set of activity or under a different environment. Therefore, a more systematic approach in activity monitoring may be of great benefit. In light of this, Mathie et al. (2004) presented a generic framework for the classification of daily activities using accelerometer signals. The framework was based on a hierarchical, binary decision tree and, thus, allowed the decision logic to be implemented in a modular manner. One advantage of this framework is that movement categories can be added or removed without affecting the other parts of the tree. Because of the independence, different algorithms can be developed for a classification task at each individual branch of the tree. An application of this framework was also presented. An activity classifier was developed to identify basic movements and simulated falls using a tri-axial accelerometer attached on the waist. Participants were tested using a standard protocol with fixed durations in a lab environment. Simulated falls measured from four healthy young individuals were identified using a rule-based algorithm. Satisfactory fall detection performance was achieved (sensitivity = 80.5%, specificity = 100%), though the detection algorithm and the types of falls were not fully described.

In 2005, Coley et al. (2005) introduced a simple ambulatory system to specifically identify walking upstairs from other daily activities. One uni-axial gyroscope was strapped to one side of the participant's shank. The validity of the proposed method to detect stair ascent was tested in real life conditions. The main idea of the proposed method was based on the characteristic backward rotation of the shank during foot-flat (stance phase) in stair ascent, which was not present in either stair descent or level walking. Corresponding to this idea, walking was first isolated from other postures and activities (Paraschiv-Ionescu, et al., 2004), and the stance phase was detected using a previous wavelet algorithm (Aminian, et al., 2002). Finally, the detection of backward angular velocity obtained from gyroscope was considered to be stair ascent activity. High sensitivity and specificity was demonstrated in this study.

A fix-threshold method is widely used to classify human daily activities. However, detailed information on actual posture threshold limits has not been clearly described. Recognizing this limitation, Lyons et al. (2005) provided a clear description of the specific posture limits for sitting, standing and lying. Two different threshold methods, mid-point method and best estimate method, were used. Preliminary testing was conducted on one elderly patient, with two bi-axial accelerometers attached on chest and thigh, respectively. It was found that the best estimate threshold method produced the most accurate posture detection results.

More recently, Nyan et al. (2006) developed a new wearable activity detection system. A bi-axial accelerometer was attached on the shoulder over the garment, rather than directly onto the skin. Wavelet techniques were used to separate the detected gait patterns into segments of level walking, ascending stairs and descending stairs. Within each segment, powers of wavelet coefficients of vertical and anterior-posterior accelerometer signals were used to determine the gait type. Twenty-two healthy participants were involved in the walking testing with little experimenter instruction. The results demonstrated excellent successful detection rate (93% to 97% in average).

In addition to the gait type detection shown above, Nyan et al. (2006) also applied the same sensor configuration and wavelet technique (Nyan, Tay, Seah, et al., 2006) to classify different postures, postural transition and gait patterns. During laboratory testing, six healthy individuals followed a standard activity protocol. The results demonstrated a satisfactory activity classification performance.

In 2006, Karantonis et al. (2006) presented another implementation of a real-time activity monitor system with fall detection capability. A tri-axial accelerometer was worn on the participant's belt, close to the right ASIS of the pelvis. The measured signals were wirelessly transmitted to a local computer via the ZigBee network. The daily activity classification algorithm was based on the framework proposed by Mathie et al. (2004). The major improvement of the proposed system was to perform the vast majority of the signal processing onboard using the embedded intelligence. A possible fall was detected whenever there were two consecutive peaks of the resultant acceleration over a fixed threshold (1.8g). The detected possible fall was furthermore verified as a real fall by detecting the inactivity for a period of time after the possible fall. Six healthy young individuals were instructed to perform activities with a standard protocol, including the simulated falls. Excellent successful fall detection rate was found, though the false alarm rate was not clearly described. The authors also acknowledged the difficulties to distinguish between fall and sitting or lying down vigorously.

2.4.2. STS motion

Functional status can be evaluated clinically by having an individual perform simple locomotor tasks (Winters & Crago, 2000). One of the most widely adopted motor tasks is sit-to-stand (STS). STS is considered one of the most functionally demanding daily activities (Kerr, White, Barr, & Mollan, 1997) and is critical for gait initiation (Munro, Steele, Bashford, Ryan, & Britten, 1998). Furthermore, the ability to rise from a chair is essential to functional independence and quality of life for the elderly (Raiche, Hebert, Prince, & Corriveau, 2000).

As a first step to acquire insight into the temporal and kinematic characteristics of the STS movements, Janssen et al. (2005) studied the accelerometer signal and its components during different types of STS motions. Accelerometers were placed on the thigh and the chest (Bussmann, et al., 2001). STS movements were performed under four conditions and normalized temporally using kinematic data. Position data from the reflective markers in optical motion analysis system (OMCS) was used to construct the sensor orientation information. Decomposition of the accelerometer signal was then achieved using the known sensor orientation. Similar characteristic trunk and thigh acceleration patterns were observed during different types of STS motions.

More recently, Boonstra et al. (2006) assessed the accuracy of measuring the angular kinematics of the upper body and thigh during rising from a chair. The sensor pack of a bi-axial accelerometer and a gyroscope was attached to the chest, pelvis and the thigh of the subject. The integration drift of the gyroscope signal was compensated by combining the low-pass filtered accelerometer signal and the high-pass filtered gyroscope signal. As expected, additional use of gyroscopes increased the angle measurement accuracy. In addition, an optimal filtering configuration for this type of motion was also determined.

Around the same time, Giansanti and Maccioni (2006) conducted the timing assessment of STS postural transition. Specifically, motion start and stop events were determined by ambulatory kinematic sensors. The kinematic sensor, comprised of a tri-axial accelerometer and a tri-axial gyroscope, was attached to the low back region of the participant. A novel adaptive threshold technique was used, with a mobile mean and standard deviation determined from the adjacent signal segments. The proposed method was validated against OMCS for both healthy individuals and individuals with pathology. Unlike the activity monitoring approaches, it was argued that the proposed system was specifically suitable for the short-term analysis of the STS motion.

2.4.3. Physical activity

Measurement of physical activity (PA) is a crucial prerequisite to understanding the association of PA with health and disease. There are four general classes of measurement approaches, including subjective reports and observations, indirect calorimetry, double-labeled water, and ambulatory monitors (Chen & Bassett, 2005). Having the advantage of being objective and able to be applied in real life situations, accelerometer-based ambulatory monitors have been extensively studied in the application of PA measurements.

The technology of ambulatory measurement in PA measurement has gone through two generations, according to Chen et al. (2005). The first generation of the PA monitor was started by Montoye et al. (1983), who first recognized the potential of accelerometers in objective PA intensity measurement. The PA monitor of this generation is usually composed of a single accelerometer attached on the waist, ankle or wrist.

Most commercialized PA monitors belong to the first generation. ActiGraph (formerly known as CSA sensor and MTI sensor) is a uni-axial accelerometer device, which is most sensitive to the vertical direction. This device can be worn at various places including waist, ankle and wrist. RT3 Triaxial Research Tracker uses piezoelectric accelerometers and measures motion in three axes. With the software provided by the manufacturer, this device was able to estimate energy expenditure (EE) using the vector magnitude of the activity counts. Actiwatch is another uni-axial accelerometer based PA monitor. It has been widely applied in sleep research. Actical, the successor of the Actiwatch, is the newest and the most miniaturized uni-axial accelerometer. Unlike other accelerometers, it has to be worn at the hip for measurement.

Multiple studies have been conducted to establish the validity of the first generation PA monitors. Freedson et al. (1998) performed a laboratory study on the validity of the ActiGraph during walking under three speeds. Using similar speeds and experimental protocols, Nichols et al. (1999) examined the Tritrac-R3D monitor while Welk et al. (2003) studied the ActiTrac and the BioTrainer monitors. These monitors were found to exhibit a strong association between the monitor counts and the measured EE. From the linear regression analysis, the variance accounted for varied from 0.82 to 0.93 for these four monitor. The resulted average EE ranged from 1.0 to 1.4 kcal per min.

Because laboratory studies are limited in representing the behavior of the PA monitors in real life situations, numerous studies also examined the validity of accelerometers in the field. However, these studies always faced the challenge of lacking a suitable validity criterion. Self-report measures are easy to use and commonly applied in field testing (Leenders, Sherman, & Nagaraja, 2000; Matthews & Freedson, 1995; Sirard, Melanson, Li, & Freedson, 2000). However, being subjective is the major limitation associated with self-report. Several researchers also tried DLW (Doubly-Labeled Water) as the validity criterion (Ekelund, et al., 2001; Johnson, Russ, & Goran, 1998); but DLW measures are unable to provide the course of changes in the EE over time.

Locomotor activities like walking have been the typical activities to validate the PA monitors. For the purpose of field testing, however, a number of studies also tried to assess free-living activities (Bassett, Ainsworth, et al., 2000; K. L. Campbell, Crocker, & McKenzie, 2002; Eisenmann, et al., 2004; Welk, Blair, Wood, Jones, & Thompson, 2000) including shoveling, raking, sweeping, etc. It was found that the PA monitors always underestimated the EE for these activities. Such underestimation was explained as the inability of waist-worn accelerometer to sufficiently monitor upper limb movements.

To solve this underestimation problem, investigators conducted calibration studies using free-living activities (Hendelman, Miller, Bagget, Debold, & Freedson, 2000; Swartz, et al., 2000). As valid as the concept sounds, the prediction power tends to be lower than locomotor tasks. In addition, there is considerable individual error associated with this approach. As one might imagine, the calibration equation is usually activity specific and infeasible and costly to be implemented in real-life situation, which there is always a combination of different activities.

Recent studies have used a set of locomotor activities and other activities to better represent the diverse nature of the free life activities that are typically encountered by younger adults (Puyau, Adolph, Vohra, Zakeri, & Butte, 2004; Treuth, et al., 2004). Combining various types of activities along with locomotor activities is certainly a good practice to ensure greater external validity; however, a single estimate equation, as used in locomotor activities, is still not sufficient to accurately characterize the data. Puyau et al. (2004) studied two types of PA monitors and found a regression equation capable to explain over 76% of the variance in measured EE. However, considering the wide confidence interval, the authors warned that resultant regression equation should not be for individual measurement.

Being small and easy to use, the first generation PA monitors are appealing in terms of high user compliance and are suitable to monitor physical activities in daily living environments. At the same time, the PA monitors of this generation also have several drawbacks. The major limitation is that they are typically composed of a single accelerometer. This makes them only sensitive to the activities relevant to the body segment that they are attached to (Chen & Bassett, 2005).

The development of the second generation PA monitors is characterized by two distinct strategies. One strategy is to utilize multiple accelerometers configuration (multiple attachment sites), which may compensate for the inability of a single accelerometer to monitor limb movement. The other strategy is to combine the various physiological sensors with accelerometer into a single device to be worn at a single place.

The development of a multi-accelerometer PA monitor was initially attempted by Swartz et al. (2000). The authors placed two accelerometers (ActiGraph) at the wrist and hip, and developed a bivariate regression equation to predict the activity EE. It was found that compared to univariate prediction ($R^2 = 0.32$) by hip sensor alone, the double-sensor approach only resulted in a marginal performance improvement ($R^2 = 0.34$). Similar multiple accelerometer approaches have also been explored with similar results (Foerster & Fahrenberg, 2000; Kiani, et al., 1998; Levine, Baukol, & Westerterp, 2001; Uiterwaal, Glerum, Busser, & van Lummel, 1998).

Recently, Zhang et al. (2004) reported the development of IDEEA, which was composed of sensors at five different placement sites. This study demonstrated the capability of IDEEA in posture and activity identification. In a subsequent study (Zhang, et al., 2003), a high correlation (>95%) between the predicted EE and measured value based on calorimetry was evident.

While the benefits of multiple-accelerometer based PA monitor may need further investigation, the associated drawbacks are apparent. Compared to single accelerometers, the multiple-sensor PA monitor are more expensive and more cumbersome due the multiple site design (Chen & Bassett, 2005).

Based on the second strategy, developments have been undertaken to combine accelerometers with other physiological sensors (e.g. HR monitor, temperature sensor, etc.) into a single PA monitor. Currently, two PA monitors using this approach are commercially available.

The Actiheart device is composed of a uni-axial accelerometer and an ECG signal sensor for the concurrent measurement of HR and body movements. This device can be attached to the chest of the user. An accelerometer/HR model was developed to predict EE during activities. A validation study (Brage, et al., 2004) has shown the significant performance increase in the predicted EE by Actiheart, compared to the estimation from HR or accelerometer alone.

The SenseWear Armband combines a bi-axial accelerometer, heat flux sensor, galvanic skin response sensor, skin temperature sensor, and a near-body ambient temperature sensor into a single device of an armband form. A complex EE prediction model was developed to incorporate the measurements from all the sensors. A validity study conducted by Jakicic et al. (2004) found that the SenseWear armband tended to underestimate the EE during locomotor activities such as walking, cycling and stepping. Meanwhile, the EE during limb activities (using arm ergometer) was overestimated. The authors suggested that further improvement in the prediction model might help resolve these issues.

Due to the single sensor design and hence single site placement, this type of PA monitor shares one common limitation with the first generation monitors, which is the inability to measure different activities with different body segment movement patterns (Chen & Bassett, 2005).

2.4.4. General approaches in daily activity classification

From the perspective of the time of data processing, the approaches of current human ambulatory measurement research can be divided into two types: non-real-time approach and real-time approach.

Non-real-time approach is popular in ambulatory measurement. In this approach, the data measurement is separated from data processing. The measurements from the portable sensors can be either stored in the on-board storage device for later retrieval or transmitted to a local computer. The on-board sensing device may include some preliminary data processing such as filtering, amplification and A/D conversion (Karantonis, et al., 2006). The core function of activity feature extraction and classification, however, are done after all the data is available. The main advantage of non-real-time type of processing is that there is no limitation on the time available to perform the data analysis. Thus, there are no constraints on the complexities of the analytical algorithms that can be implemented. More importantly, since all the data is available at the time of processing, the current motion can be determined using the information regarding the future events. For example, in a walking pattern recognition study (Najafi, et al., 2003), the postural/motion transition point was first detected and recognized, and the posture/motion during the period adjacent to the transition point was then identified. This type of analysis will not be feasible if the entire dataset is not available.

In the real-time approach, the data analysis is performed simultaneously with the data capturing, with or without certain amount of time delay. Compared to the non-real-time approach, real-time analysis is less frequently used due to its inherent limitations. The time constraints impose strict limitations on how complex and time-consuming the analytical algorithm can be. Furthermore, just opposite to the non-real-time analysis, there is no or limited information regarding the future events that can help the determination of the current activity. There is also a limited buffer size for an ambulatory device, which means the availability of previous data is also restrained. However, the real-time approach is the only choice for time-critical applications like fall event detection. This is also the dominating factor that simple threshold detection algorithms are adopted in most fall detection studies.

2.5. Ambulatory gait analysis

2.5.1. Gait event detection

At the beginning of 90's, Willemsen et al. (1990) demonstrated the possibility to detect swing and stance phases during normal gait with a single uni-axial accelerometer attached on the shank. However, this approach was found to be sensitive to the large acceleration disturbance present on patients using crutches.

Later, along with detecting simple body postures, Walker et al. (1997) proposed a method to detect the number of steps during walking with a chest-mounted accelerometer. Step detection was achieved by detecting the trunk vertical impulse during heel contact, together with a rule set to prevent issues like miscount and double count.

Entering the 21st century, Williamson and Andrews (2000) applied two commercially available supervised machine learning programs to the signal obtained by a three-accelerometer cluster to determine both stance/swing phases and multiple gait events. The applied machine learning programs, Rough Sets and Adaptive Logic Networks, were first trained with reference dataset. The detection performance on novel dataset was validated against the results from FSRs. A detection accuracy of 84.8% was achieved, which was considered by the author to be sufficient in FES control applications. The application of this system remained to be tested in the outdoor environment as well as during walking on irregular surfaces, slopes and stairs.

Pappas et al. (2001) further presented a so-called portable gait phase detection system (GPDS) that could provide information about multiple gait phases during walking for closed-loop FES walking applications. The GPDS consisted of three FSRs on the shoe insole and a miniature rate gyroscope on the heel of the foot. Four gait phases (stance, heel-off, swing, and heel-strike) were modeled by a state machine with four distinct states and seven allowable transitions. High detection accuracy (96%~99%)

were achieved for both healthy and pathological gait and for a variety of surfaces/walking conditions (irregular surface, slope, stair climbing, etc).

In 2003, Mansfield et al. (2003) attempted to detect gait events by changes in trunk acceleration patterns. One bi-axial accelerometer was placed on the lower back. Negative to positive change of AP acceleration was regarded as heel contact. The heel contacts detected by accelerometers presented a consistent delay (in average 150ms) with a large variation. It was claimed this was the first study to report the automated determination of heel contact events based on the analysis of acceleration curves of body COM.

At the same time, Zijlstra and Hof (2003) investigated the feasibility to estimate spatio-temporal gait parameters from lower trunk accelerations. A single tri-axial accelerometer was placed near the low back. Participants walked on the treadmill at five different speeds and on the ground as well. Heel contact events were detected as the occurrence of peak amplitude preceding the change of sign in AP acceleration. Left and right steps were detected from the first harmonic of the medio-lateral displacement, which was obtained by integrating the medio-lateral acceleration signals. This distinction was not always successful, though. Step length was estimated by the vertical change of height and an inverted pendulum model. However, step lengths were always underestimated, which in turn, resulted in the underestimated walking velocities. This study is very attractive for its simple sensor configuration (one accelerometer on lower back) and the straightforward analytical approach.

In 2004, Aminian et al. (2004) proposed a new ambulatory gait analysis system and examined the applicability of this system as a complementary method of gait analysis after hip arthroplasty. The proposed system (i.e. Physilog) was composed of four gyroscopes attached to each shank and thigh. Spatio-temporal gait parameters were determined using previous wavelet-based algorithm (Aminian, et al., 2002). In addition, ranges of rotation of each thigh and shank segment and knee joint were estimated and compared with those derived from OMCS. This study demonstrated the clinical usefulness of the portable gait analysis device on the hip replacement patients.

More recently, Jasiewicz et al. (2006) compared the performances of three gait event detection methods in both healthy individuals and spinal-cord injured patients with pathological gaits. Four sensor packs (each comprised of one gyroscope and one tri-axial accelerometer) were attached onto each foot and shank of the participant. Nineteen healthy individuals and thirteen patients were involved in the testing. Three methods were proposed, based on signals from foot accelerometer, shank gyroscope and foot gyroscope, respectively. Results indicated that for normal individuals, all three methods performed equally well. In contrast, for abnormal foot steps, both foot acceleration and foot angular velocity based methods were considerably more accurate than the shank gyroscope based method. It could be inferred that if pathological gait was to be analyzed, methods based on sensor signal from foot segment were more suitable.

2.5.2. Spatio-temporal gait parameters estimation

Spatio-temporal parameters such as stride length and walking velocity were commonly estimated because they provide the most basic functional information about gait (Miyazaki, 1997). In addition, this information can be easily used to derive more sophisticated gait parameters to accommodate different application scenarios.

In 1995, Aminian et al (1995a, 1995b) performed the first set of studies to assess the walking speed with accelerometers. Their objective was to explore the capability of accelerometers in predicting walking speed under a variety of conditions. A tri-axial accelerometer (fused by three uni-axial accelerometers) and a uni-axial accelerometer were placed on the lower back region and on the top of the right heel, respectively. Data from five healthy participants were collected during treadmill walking at seven different inclinations and three different speeds (normal, fast and slow), in an outdoor condition. In this study, heel contact events were estimated by searching for the negative peaks of heel vertical acceleration. Basic statistics (mean, variance and covariance) of trunk 3D acceleration were performed for each gait cycle (determined by heel contact information). It was recognized that the acceleration-based parameters correlated nonlinearly with walking speeds and inclinations, and were strongly influenced by individual's walking style. In light of this limitation, an artificial neural network (ANN) was applied and good agreement between predicted and measured speed and inclination were found. The authors also indicated that sufficient number of walking patterns has to be provided for ANN training in order to achieve satisfactory prediction accuracy.

In order to facilitate the effectiveness evaluation of pharmacological and surgical treatments in rehabilitation, Miyazaki (1997) estimated step length and walking velocity with a piezoelectric gyroscope attached on the thigh. The relative thigh sagittal range of motion was computed by integrating the gyroscope signal, together with a physical min/max detector. A short integration time window (2s) was adopted to avoid drifting error associated with the integration process. Assuming a simplified, single segment gait model, step length can be approximated from the known leg length and the measured thigh range of motion. Walking velocity can then be estimated. An individual calibration procedure, however, had to be performed to obtain the compensation coefficient to adjust estimation error. The author also expected that such calibration had to be conducted under different walking environments (ex. surfaces with different inclinations).

To fulfill the need for a more detailed ambulatory measurement, Moe-Nilssen (1998a, 1998b) made the first thorough investigation on the accelerometer performance as well as their feasibility in gait analysis. In the first part of this two-series of study, the author provided a clear description of static and dynamic calibration procedure for the accelerometer. One tri-axial piezoresistant accelerometer was placed in the lower back region. By assuming the constant (or negligible changes) orientation of the attached accelerometer in space during walking, Moe-Nilssen proposed a detailed mathematical algorithm to transform any arbitrarily tilted accelerometer into a vertical-horizontal coordinate system, which greatly facilitated the accurate utilization of accelerometer measurement. The validity of this algorithm, however, appeared to be restricted to lower back mounted accelerometer during walking conditions.

In the second part (Moe-Nilssen, 1998b) of the same study, the trunk accelerometer signal was used to evaluate balance maintenance in walking under real life conditions. The author questioned the appropriateness of using COP-based static balance measures as the indicators of dynamic balance during walking. The RMS value of the accelerometer signal during walking was studied in relation to different walking speeds. The author believed that by mounting the accelerometer at a surface point (L3 process of the spine in their case) close to body COM, the linear kinematics of body COM could be adequately estimated. It was confirmed that the sagittal trunk inclination during standing was not representative of the one during walking, and the inclination during walking is strongly correlated with walking speed. Another interesting contribution from this study was the normalization procedure of the walking velocity. By taking measurements at various speeds and estimating an individual quadratic fit curve, the expected measurement at a specific walking speed can be interpolated within the range demonstrated by that individual.

Applying the same methodology (Moe-Nilssen, 1998a, 1998b), Moe-Nilssen (1999) studied the walking motor behavior change induced by experimental low back pain (LBP) using accelerometer. After tilt correction, the accelerometer RMS values during walking were compared before and after

LBP conditions. Significant reduction in the trunk acceleration RMS was found, which confirmed the utility of accelerometer in detecting walking behavior adjustment after experimental LBP.

Based on the findings from their previous research (Aminian, et al., 1995a, 1995b), Herren et al. (1999) extended the ambulatory measurement from laboratory settings to outdoor running conditions. Tri-axial accelerometer signals from the lower back and the heels, together with ANN technique, were used to recognize running patterns and to estimate the running speed and the surface inclination. It was found that the running speed and the terrain inclination could be estimated with sufficient accuracy, which could be used to complement the ambulatory monitoring of energy cost associated with physical activity.

Strong correlation between walking speed and accelerometer output has been revealed during level walking or as long as the inclination of the walking surface is constant (Aminian, et al., 1995a, 1995b). It is then suggested that accelerometer can be used to predict walking speed, if additional information on the surface inclination is given. According to this rationale, Perrin et al. (2000) tested whether the combination of altitude measurement from differential barometry with the body acceleration information provided by trunk accelerometer could improve the walking speed prediction. The speed of walking and the slope of the surface were validated in outdoor by GPS system. It was found that adding altitude variation greatly improved the speed prediction accuracy.

Though it has long been a known fact that an accelerometer signal is composed of both inertial component, which is of interest in most gait analyses, and gravitational component, Bussmann et al. (2000) conducted the first thorough study to understand the characteristics of different accelerometer signal components during normal walking. A uni-axial accelerometer was attached on the thigh of one participant. The measured acceleration was compared with the reconstructed acceleration from OMCS while the participant walked at three different speeds. Characteristics of gravitational and inertial accelerations, as well as different sub-components of inertial acceleration, were examined. Gravitational and inertial components of the accelerometer output were confirmed to differ in frequency. Therefore, in theory, it is possible to separate these two components using a filtering technique.

In 2002, Aminian et al. (2002) proposed a wavelet-based algorithm to detect gait events from shank angular velocity. In addition, a double segment model, which considered a double pendulum model during the swing phase and an inverted double pendulum model during stance, was proposed to estimate spatial parameters like stride length. Gyroscopes were attached on both shanks as well as the right thigh. Participants involved both young and elderly individuals. High gait event detection accuracy (less than 5ms for 95% confidence interval) was achieved. The estimation error for velocity and stride length was found to be around 7%, which was speculated to be mainly caused by the integration error of gyroscope.

At the same time, Auvinet et al. (2002) established a reference dataset for several gait parameters using accelerometers from a large sample of healthy individuals (138 males and 144 females). Measurements were conducted in a long walkway to ensure stable walking. Acceleration data was used to estimate stride frequency, gait event, gait symmetry and regularity. This study demonstrated the utility of an ambulatory system in gait analysis, though the accuracy and reliability of the algorithm used in this study were not clear.

Though several methods have been proposed to perform gait analysis using accelerometer or gyroscopes, none of these methods has investigated the possible influence of different walking speeds. In 2004, Moe-Nilssen and Helbostad (2004) suggested a protocol of estimating common gait parameters using a tri-axial accelerometer. In addition, they described a technique to control for different walking speeds. As a convention for this research group, a single tri-axial accelerometer was placed over the low back region. Unbiased autocorrelation algorithm was used to estimate cadence, gait regularity and symmetry. A curve estimate was calculated over a range of speeds for each gait parameter and each individual. A point estimate at a specific walking speed was then obtained by interpolating the curve estimate. The proposed methodology in this study is interesting because it is capable of estimating the number of steps without detecting the exact gait events. Its application, however, may be limited because parameters like walking distance and walking speeds still have to be measured by other instruments.

Recently, Henriksen et al. (2004) evaluated the relative and absolute test-retest reliability of a trunk accelerometer gait analysis procedure designed to estimate various common gait parameters. Using the same unbiased autocorrelation algorithm (Moe-Nilssen & Helbostad, 2004), various gait parameters were estimated. Test-retest reliability was evaluated using the intra-class correlation coefficient (ICC). It was found that the reliability of such trunk accelerometer gait analysis approach was satisfactory.

At the same time, Salarian et al. (2004) developed a new method for ambulatory gait analysis in patients with Parkinson's disease. Ten uni-axial gyroscopes were attached at six sites (one on each thigh and shank, three on each forearm) of the body. Temporal gait events (initial contact and terminal contact) were determined by the characteristic peaks presented in the shank angular velocity. Lower extremity ranges of angle were calculated by integrating the gyroscope signals measured from the shank and thigh. Similar double-segment model (Aminian, et al., 2002) were used to estimate stride length and walking velocity. Compared with a previous wavelet-based algorithm (Aminian, et al., 2002), the proposed method produced higher precision for temporal event detection. But the spatial parameter estimation was less accurate. Most importantly, this new algorithm performed nine times faster than the previous algorithm, which would be particularly meaningful in situations requiring real-time processing.

One year later, Sabatini et al. (2005) described an IMU-based ambulatory monitoring system to estimate spatio-temporal gait parameters during walking. The IMU was composed of one bi-axial accelerometer and one rate gyroscope, placed on the instep of the foot. Four gait phases (stance, heel-off, swing, and heel-strike) were detected by thresholding the foot angular velocity measured by the gyroscope. Acceleration information during the stance phase was used to remove the uncertainty in estimating the initial angles. Sagittal position and orientation of the foot segment was estimated by strap-down integration of the IMU signal. Five healthy participants were tested at various walking speeds and surface inclinations. The performance of the proposed system in gait phase detection was found to be comparable with those analyzed using wavelet technique (Aminian, et al., 2002).

Recognizing that the location and orientation of the attached accelerometer can have a large influence on the measured signal, Kavanagh et al. (2006) studied the intra- and inter-examiner reliability, and stride-to-stride reliability of accelerometer measurements in gait analysis. The coefficient of multiple determination (CMD) which was one type of waveform reliability statistic, was applied in order to taking into account the time-series evolution of the signal. Four tri-axial accelerometers were attached at four different segments of the body (head, neck, trunk, and shank). The results indicated that experienced examiners were equally able to replicate the location and orientation of the accelerometers across different test sessions.

Ambulatory gait analysis has always been conducted on adult population. However, gait analysis on children is also of interest during some occasions. Recently, Brandes et al. (2006) investigated the validity of an accelerometer-based gait analysis system on children. Previous methodology (Zijlstra & Bisseling, 2004; Zijlstra & Hof, 2003) using inverted pendulum model and the signal from a tri-axial trunk accelerometer was applied to obtain step length and walking distance.

2.5.3. Other gait analysis applications

Besides the gait event detection and regular spatio-temporal gait parameter estimation, ambulatory measurement methodology has also been used in other gait analysis applications including joint kinetics assessment and gait variability evaluation.

In 2004, Zilstra and Bisseling (2004) developed a method to determine the hip abduction joint moment based on accelerometers and gyroscopes. The performance of two models, one with a single rigid trunk assumption (vandenBogert, Read, & Nigg, 1996) and one with a two-segment trunk assumption, were evaluated. By attaching one tri-axial accelerometer and one gyroscope onto the upper and lower trunks respectively, the segmental linear and angular accelerations became available. The two proposed models produced moderate to good agreement with the results obtained from traditional inverse dynamics approach.

In 2005, Beauchet et al. (2005) investigated the effects of two different cognitive tasks on stride-to-stride variability on frail elderly. The previous developed ambulatory system (Aminian, et al., 2002) was used to measure the variability of stride duration. It was found that, under a dual-task condition, stride time variability was influenced by the type of concurrent spoken task.

Similarly, Dubost et al. (2006) investigated the relationship between stride time variability and the simultaneous attention-demanding task during walking. Previously validated gyroscope-based ambulatory gait analysis system was used to measure the stride time variability. It was found that, for the healthy older adults, the dual-task related increase in stride time variability was correlated with attention demanding task, thereby providing the evidence for certain attention control in rhythmic stepping mechanism.

2.6. Ambulatory fall risk assessment

Fall risk assessment is important for two reasons. First, knowledge of the risk profiles could provide a basis for early detection of potential fallers (Bloem, et al., 2003). Second, given the variety of the risk factors for falling, risk profiles are very likely to vary between individuals. Accurate assessment of individual falling risks provides targets for choosing the most appropriate fall intervention solutions. The fundamental tenet for this assessment approach is that performing a fall-risk assessment is likely to reduce the possibility of future falls when coupled with appropriate intervention (Lundebjerg, et al., 2001). Any fall-risk assessments include not only the evaluation of an individual's intrinsic factors (i.e. physiological and psychological status), but also extrinsic factors (i.e. living environment). Recommendations on fall-risk assessment methods and procedures, specifically designed for the elderly, have been proposed by an international consensus panel (Lundebjerg, et al., 2001) in the medical domain.

The core problem in fall-risk assessment is the identification of suitable parameters or measures corresponding to an individual's falling risks. Up to now, those parameters that have been studied by various investigators can be identified to be associated with three aspects: postural stability (e.g. standing balance), gait spatio-temporal features (e.g. spatio-temporal gait parameter variability), and postural transition (e.g. sit to stand motion).

2.6.1. Assessment through postural stability

Finding a suitable parameter to accurately represent an individual's postural stability and thus his/her risk of falling has been recognized as an important task (Giansanti, 2006). Postural stability is governed by complex internal neuromuscular models (Morasso, Baratto, Capra, & Spada, 1999) and has been long suggested to be correlated with an individual's fall risk. Conventionally, parameters derived from the displacement of COP measured by force-plates are widely adopted as indicators of postural stability. However, acceleration of body COM has been suggested to be a more adequate measure of balance (Moe-Nilssen, 1998c). Naturally, whether it is feasible to apply ambulatory measurement in postural stability assessment becomes one necessary step towards fall risk evaluation using ambulatory sensors.

In 1998, Moe-Nilssen (1998c) performed the first static and dynamic balance study using an accelerometer. A tri-axial accelerometer was placed on the lower back. After tilt correction (Moe-Nilssen, 1998a), the acceleration RMS from each sensitive axis was measured from multiple standing conditions and from walking at different speeds. Because this study was focused on the test-retest reliability, no discriminative validity was tested.

In 2002, Moe-Nilssen et al. (2002) investigated the discriminative validity of using the trunk accelerometer signal as a standing balance measure. Two groups of participants (young and old) were subjected to multiple testing conditions with different levels of challenges. True horizontal acceleration was estimated based on the assumption that the best estimate of mean acceleration over time during unperturbed standing will be zero along any axis. Discrimination between different testing conditions has been successfully demonstrated.

At the same time, Mayagoitia et al. (2002) also conducted a standing balance study using accelerometers. A tri-axial accelerometer was used to measure the acceleration at the approximate level of body COM. Together with the known height of the sensor, the horizontal coordinates of resultant acceleration projected on the floor was obtained. The same set of parameters based on the projected tracing from accelerometer and the COP measurements from the force-plate were compared. The accelerometer-based balance parameters showed better discriminative ability than those from force-plates.

Though the above research can be implied to be relevant with fall-risk research, it is only recently that one study was carried out to explicitly associate ambulatory balance testing with the risk of falling in the elderly (Giansanti, 2006). In this study, one kinematic sensor (combination of tri-axial accelerometer and tri-axial gyroscope) was attached on the low back of the participants. Kinematic rotational energy changes during quiet standing in three different conditions were calculated based on the measured angular velocity. The measurements were taken from three participant groups (healthy young, healthy elderly and frail elderly) with different levels of fall risk as determined by the Tinetti test. Satisfactory performance in fall risk differentiation was achieved.

2.6.2. Assessment through dynamic activities

The second aspect of fall-risk assessment involves an individual's ability to carry out postural transition successfully. It has been reported that many falls in stroke patients happen when they change position (e.g. standing up, sitting down or gait initiation) (Nyberg & Gustafson, 1995). In a study evaluating the effect of different rising speeds, it has been demonstrated that factors including subjects' age may influence the whole-body dynamics during sit-to-stand motion (Pai & Rogers, 1990). As one of the most functionally demanding daily activities, STS motion may correlate with fall risks.

Najafi et al. (2002) evaluated STS transition motion and their correlation with risk of falls using the gyroscope. The wavelet technique was adopted to analyze trunk tilt during STS motion. Only one gyroscope was attached on the chest. Three parameters (mean and SD of postural transition duration, and the number of successive attempts) produced by the ambulatory system were used to differentiate groups with a low and high risk of falling (as determined by fall history and Tinetti balance and gait disorder score). It was clearly shown that the temporal parameters during postural transition could differentiate groups with different fall risks. On the contrary, types of postural transition (sit-to-stand or stand-to-sit) did not seem to have a specific influence.

The risk of falling can also be correlated with gait spatio-temporal features. In particular, step length and walking velocity reduction as well as their variability have been associated with the fear and risk of falls (Maki, 1997). In the area of ambulatory measurement, a few attempts have been made to investigate the feasibility to assess fall risks using gait parameters.

In 2001, Najafi et al. (2001) evaluated the gait features in 25 elderly participants. These elderly were divided into three groups based on various degrees of fall risk. Gyroscopes were employed to estimate regular gait parameters including walking velocity, step length, stance time, etc. The results showed a significant group effect in many of the gait parameters. In addition, the spatio-temporal gait parameters were found to correlate well with the Tinetti's score, suggesting the feasibility to assess fall risk with the ambulatory gait analysis approach.

In 2005, Moe-Nilssen et al. (2005) investigated whether inter-stride trunk acceleration variability could effectively differentiate fit elderly and frail elderly. The latter group was believed to have a higher risk of falling. Gait parameter variability has long been considered to be an indicator of individual balance control capability. Naturally, whether variability assessed by ambulatory measurement can predict fall risk becomes an interesting question. One tri-axial accelerometer was attached to the trunk. Autocorrelation coefficients (ACORR) were calculated for each of the three sensing axes. The confounding effect of different walking velocities on the outcome measures was controlled for by individual curve estimation (Moe-Nilssen & Helbostad, 2004). The results indicated the ACORR at both AP and ML directions as significant discriminating variables (sensitivity = 0.75, specificity = 0.85). Therefore, trunk acceleration variability demonstrated strong ability in discriminating the elderly with greater risk of falling.

2.7. Ambulatory measurement in general biomechanics

Starting from the late 90's, Tong and Granat (1999) explored the possibility of estimating joint and segment angular kinematics during walking from uni-axial gyroscopes. Two gyroscopes were attached to shank and thigh segments. Joint angle and segment inclination estimated by integrating gyroscope signals were compared with those measured by OMCS. Two methods, auto-reset during gait cycle and high-pass filter, were applied to correct for drifting error, especially during turning. Excellent curve similarity (correlation coefficient > 98%) was achieved. In addition, it was found that the gyroscope measurement was not location specific as long as it was placed along the same plane on the same segment.

Recognizing the integration error associated with the angle estimation from rate gyroscopes, Williamson et al. (2001) developed a methodology combining signals from both accelerometers and gyroscopes. The signal from the rate gyroscope was integrated to produce an estimate of angle. Accelerometers were used to compensate for slowly occurring errors in the integral of the rate gyroscope. The combination of two error correcting (auto-resetting) and three offset correcting (auto-nulling) techniques were explored and compared to those estimated by the goniometer and accelerometer. All the methods were applied to measure knee joint angle and angular velocity during STS motion. Satisfactory results with error level less than 4° were achieved. It was found that the auto-nulling technique may remove the strict requirement of a calibration period prior to each test. In addition, since the rate gyroscope signals are integrated to produce an estimate of angle, the signal did not need to be low-pass filtered, which can add delay and inaccuracy to the estimate. Compared to estimating angles from goniometers, combination of an accelerometer and gyroscope did not require further calibration after the sensor attachment.

Mayagoitia et al. (2002) presented a methodology using a gyroscope and accelerometer to measure segment and joint kinematics (including shank angle, angular velocity, angular acceleration, and knee linear acceleration) in the sagittal plane. Two bi-axial accelerometers and one uni-axial gyroscope were mounted on one segment. Measurements were taken from 10 healthy young individuals at five different speeds during walking. Good agreements were achieved between angular kinematics obtained by sensors and those obtained by OMCS. Considerable error, however, was observed for knee linear acceleration. This error was considered to be due to the sensor being hit or vibrated during heel contact.

At the same time, Bemmark et al. (2002) demonstrated the utility of the accelerometer in monitoring arm elevation. Specifically, the arm inclination with respect to the vertical line was measured by a tri-axial accelerometer mounted over the deltoid muscle on the upper arm. The results were compared with those obtained by OMCS. The objective of this development was to measure the posture and movements during occupational work, e.g. before and after the introduction of an ergonomic intervention program.

In 2003, Lee et al. (2003) explored the feasibility of using tri-axial gyroscopes to measure three dimensional lumbar spine motion. Two tri-axial gyroscopes were attached to the L1 spinous process and the sacrum, respectively. The relative orientation between L1 and sacrum was used to represent the lumbar spine motion. Using the information provided by the built-in magnetometer and gravitometer, together with the Kalman filter, the drifting error associated with the integration process was corrected. This study claimed a successful attempt to obtain 3D orientation from tri-axial gyroscopes, though the mathematical algorithms were not clearly described in detail.

One problem with accelerometers is that they suffer from a fluctuating offset. Though this problem can be solved by off-line, explicit calibration procedure, it is highly desirable to have a continuous online implicit calibration procedure in the application of ambulatory monitoring. In 2004, Luinge and Veltink (2004) proposed a method to continuously estimate the offset component of a tri-axial accelerometer. A discrete-time, complementary Kalman filter was designed to separate the gravity, acceleration and offset components from the accelerometer output, based on the signal characteristics associated with each component. A crate-lifting task was chosen to test the proposed algorithm. It was found that the inclination estimation error produced by the proposed algorithm was significantly smaller than that produced using the low-pass filtered data. This performance improvement was concluded to be attributed to the assumption that the acceleration can be described by a band-pass characteristic.

It is a common approach to integrate the gyroscope signals in order to obtain the angle. Though various methods have been proposed to eliminate the drifting error associated with the integration process, they all have the problem of removing both the dc and low frequency information of the angles. To solve this problem, Dejnabadi et al. (2005) proposed a new method to measure joint angle using the concept of a virtual sensor. One IMU (combination of one bi-axial accelerometer and one gyroscope) was placed on each shank and thigh. A virtual sensor at the knee joint center of rotation was predicted by shifting the IMUs on the adjacent segments (thigh and shank) mathematically. Knee sagittal joint angle was then estimated by the orientation of the predicted virtual sensor. Validation data was obtained during level treadmill walking at different speeds. Excellent joint angle estimation was achieved (mean = 0.2 degree, SD = 1.1 degree). The advantage of the proposed method was that no integration process was involved and thus the drifting error was eliminated. However, this method required individual anthropometric information and the IMU position data.

Having recognized the potential benefit of incorporating gyroscopes with accelerometers to estimate the orientation (Luinge & Veltink, 2004), Luinge and Veltink (2005) further designed and evaluated a Kalman filter that fused tri-axial accelerometer and tri-axial gyroscope signals together to measure the body segment orientation. The orientation was obtained in a statistically most-likely sense, with assumptions about the target movement and the sensor error behavior. More accurate orientation measurement was achieved as opposed to the approach using accelerometer only. The authors also acknowledged two limitations. First, if accurate heading information is required, additional sensor (ex. magnetometer) or movement assumptions have to be made. Second, the presented IMU would have limited ability to track large temperature fluctuations which are common in real-life field tests.

Meanwhile, other research groups also devoted their effort in the development of the IMU sensor and the associated algorithm. In 2005, Giansanti et al. (2005) developed their IMU, which was composed of three rate gyroscopes and three accelerometers, and performed a bench test and a clinical validation to evaluate the sensor's ability to reconstruct position and orientation information during a locomotion task. The authors argued that the developed IMU had the advantage of being model-independent and requiring no a priori knowledge of the target movement.

About the same time, Simcox et al. (2005) also presented their accelerometer and gyroscope combination sensor pack, which was conceptually an IMU. The development was aimed towards FES application. The sensor pack was composed of one uni-axial gyroscope and a tri-axial accelerometer. The orientation estimation was based on the comparison of the integrated angular velocity from the gyroscope to the tilt from the accelerometers, in order to minimize the drifting error associated with the integration. Five sensor packs were strapped onto the participant's chest, thighs and shanks. Overall, the concept of this study was very similar to those previously presented (Luinge & Veltink, 2004).

In 2006, Zhou et al. (2006) developed an inertial sensor-based motion tracking system to measure the location of the upper limb in space. Signals from accelerometer and gyroscope were fused together. Different from the commonly adopted Kalman filter, an optimization algorithm (i.e. fast simulated annealing), together with physical constraints, was adopted to minimize the integration drift in order to obtain accurate position measurements. The physical constraints were imposed by a two-segment anatomical model. Substantial improvement in position estimation accuracy was evident.

Recently, Luinge et al. (2007) derived a method for drift-free estimation of the orientation of the two arm segments using inertial sensors and anatomical elbow constraints. The purpose of this study was to evaluate the impact of neuromuscular disorders affecting the functional use of the upper extremity. A calibration method was required to provide the exact orientation of each sensor relative to the segment. Preliminary results indicated a considerable decrease in orientation error.

2.8. Summary

2.8.1. Fall epidemiology

The most important and obvious consequences of fall accidents are physical injuries, including those (e.g., hip fracture, upper extremity injuries, etc.) sustained from the fall impact directly and/or those (e.g., long-lie) caused by lack of timely medical assistance. In addition to physical injury, fall accidents can also have psychological and social consequences including loss of independence, fear of falling, reduction of physical activity, etc.

There are potentially over 400 factors, which can be classified into intrinsic and extrinsic factors, contributing to the risk of falling. Fall risk factors can also be classified differently according to different researchers. It is generally agreed, however, that effective fall prevention has to be a multidisciplinary effort.

2.8.2. Fall event detection

As summarized in Table 1, the existing research associated with fall event detection has the following characteristics: 1) in terms of the target of detection, majority of the studies were detecting falls based on the post-impact mobility features; 2) most of the studies were evaluating the detection performance with the young participants; and 3) most of the testing protocols involved various types of voluntarily falling from static posture (i.e., standing). However, the site of sensor attachment featured various designs, though somewhere on the trunk segment was a common choice.

Table 1 – Summary of fall event detection literatures

Research	Target of detection	Testing subjects	Fall testing protocol	Detection criteria	Site of attachment
Williams et al., 1998	Impact				
Doughty et al., 2000	Post[1]	Mannequin			
Noury et al., 2000	Post			Acc[4]	
Noury et al., 2003	Post	Young	voluntary/static[3]	Acc	Belt
Degen et al., 2003	Post	Young	voluntary/static	Acc	wrist
Hwang et al., 2004	Post	Young	voluntary/static	Acc	chest
Diaz et al., 2004	Post	Young	voluntary/static	Acc	upper back
Lindemann et al., 2005	Post	Young	voluntary/static	Acc	behind ear
Nyan et al., 2006a	Post			Acc	
Karantonis et al., 2006	Post	Young	voluntary/static	Acc	Belt
Nyan et al., 2006b	Pre	Young	involuntary/static	Gyro	sternum, shoulder, underarm
Bourke et al., 2007a	Post	Young/Elderly[2]	voluntary/static	Acc	trunk, thigh

[1]Post: post-impact detection; pre: pre-impact detection
[2]Elderly was involved for ADL testing only.
[3]voluntary (involuntary)/static: voluntary (involuntary) fall from static posture
[4]Acc: accelerometer; Gyro: gyroscope

Despite the continuing efforts endeavored in fall event detection, current designs have several limitations that need to be addressed before the effective application can be achieved. These limitations include two efficacy issues (i.e., the balance between misdetection and false alarm), the unclear target of detection, and issues with performance evaluation process.

2.8.3. Ambulatory sensors

Ambulatory measurement applications often utilize six types of ambulatory sensors: accelerometers, gyroscopes, magnetometers, pedometers, force sensitive resistors, and goniometers. Among these sensors, accelerometers and gyroscopes are most commonly used.

Most accelerometers are capable of measuring the acceleration induced by the dynamic activity, and the gravity. Because of the sensitivity of the gravity, an accelerometer can be used as an orientation sensor under static or quasi-static conditions. Such sensitivity, however, make it difficult to isolate the desired signal relevant to the activity of interest under dynamic conditions.

Without being affected by the gravity, gyroscopes represent another promising choice of ambulatory sensors. They are also less noisy than accelerometers and not sensitive to the location of attachment. Being expensive and prone to drifting errors, however, are the major challenges faced by the gyroscopes.

The utility of the rest four types of sensors is relatively limited, compared with accelerometers and gyroscopes. Magnetometers are usually incorporated with other sensors for error correction purpose. Force sensitive resistors are usually adopted to facilitate gait event detection. Goniometers are facing issues like cross talk, lack of robustness, etc. Pedometers have been widely applied to assess the level of physical activity. However, pedometers are unable to provide information regarding the type or the pattern of the activity and thus have limited accuracy in the activity level assessment.

2.8.4. Ambulatory daily activity classification

The existing literature on daily activity classification can be roughly divided into three application domains: activity monitoring, STS motion assessment, and PA measurement. Activity monitors can be used to provide an objective indication of the activity levels or restrictions experienced by patients or elderly. Ambulatory assessment of STS motion, which is considered one of the most functionally demanding daily activities, can be used to evaluate an individual's functional status, which is essential to functional independence and quality of life for the elderly. Being able to measure PA objectively and in real life situations is a crucial prerequisite to understanding the association of PA with health and disease.

There are two general data processing approaches in daily activity classification. One is the non-real-time approach, which is popular in most of the ambulatory measurement applications. This approach does not restrict the time available to perform the data analysis and thus the complexities of the analytical algorithm that can be implemented. The real-time approach, though less frequently used, is the only choice for time-critical applications including fall event detection, which is the focus of this dissertation research.

2.8.5. Ambulatory gait analysis

Most of the existing research on ambulatory gait analysis focused on the gait event detection and the spatio-temporal gait parameters estimation. In order to achieve high estimation accuracy, researchers either adopted sophisticated hardware design which usually incorporated multiple ambulatory sensors at multiple body segments (e.g., Aminian, et al., 2002), or relied on assumptions of normal gait patterns explicitly or implicitly (e.g., Mansfield & Lyons, 2003). Both ways have inherent limitations: utilizing more sensors may hinder the user compliance while assumption of normal gait patterns makes it infeasible to be applied to patients with gait pathology.

2.8.6. Ambulatory fall risk assessment

The core problem in fall-risk assessment is the identification of suitable parameters or measures corresponding to an individual's falling risks. Biomechanically, three categories of parameters (i.e., postural stability, gait spatio-temporal features, and postural transition) have been identified to be associated with an individual's risk of falling. Consequently, ambulatory fall risk assessment mainly focused the connection between fall risk with standing balance (Moe-Nilssen & Helbostad, 2002), gait parameters (Najafi, et al., 2001), or the functional ability for STS (Najafi, et al., 2002).

2.8.7. Ambulatory measurement in general biomechanics

Ambulatory measurement technology has also been applied in general biomechanics research, which include joint and segment angular kinematics assessment (Mayagoitia, Nene, et al., 2002; Tong & Granat, 1999), arm elevation measurement (Bernmark & Wiktorin, 2002; Zhou, et al., 2006), 3D lumbar spine motion evaluation (Lee, et al., 2003), and IMU development (Giansanti, et al., 2005; Luinge & Veltink, 2004, 2005; Simcox, et al., 2005). All these research were motivated by the advantages (e.g., portable, power-efficient, cost-effective, etc.) of ambulatory sensors over conventional laboratory-based measurement systems.

Chapter 3

3. METHODOLOGY

3.1. The integrative ambulatory measurement (IAM) framework

The concept of the IAM framework is to integrate both the real-time and the non-real-time processing capabilities together, to split the functions of the target application, and to allocate individual functions to the most appropriate processing module. It is expected that such a framework will maximize the efficacy of each individual processing module and optimize the performance of the target application.

In terms of human activity classification, as stated in the Chapter 1, most of the daily activity recognition scenarios are not time critical and are suitable to be processed in a non-real-time manner. For a few other applications including fall event detection, rapid response is of one of the top priorities, which dictates that fall accidents can only be detected in a real-time manner.

In addition to simply putting two processing modules together, the IAM framework also emphasizes the importance of being able to share information between the real-time and the non-real-time modules. The real-time module is responsible for capturing and storing the data to be further processed by the non-real-time module. Meanwhile, the non-real-time module should be able to provide feedback to update some critical parameters in the real-time module so as to improve the real-time processing performance.

In the current study, the fall event detection was taken as a representative application of the IAM framework. This particular application was expected to show the feasibility and utility of this framework. As illustrated in Figure 2, the core component of this application, fall detection function, is allocated to the real-time processing module. Specifically, the real-time module of the IAM framework is responsible for fall detection and data storage during up-time, which is defined as the period when the fall detector is functioning (i.e. during day time). A new fall detection algorithm is implemented in this module. Simultaneously, the real-time module also controls the data storage unit, which saves the obtained data into on-board memory without processing. These stored data is transferred and processed in the non-real-time module during nap-time which is defined as the period when the active functioning is not required (i.e. during night time).

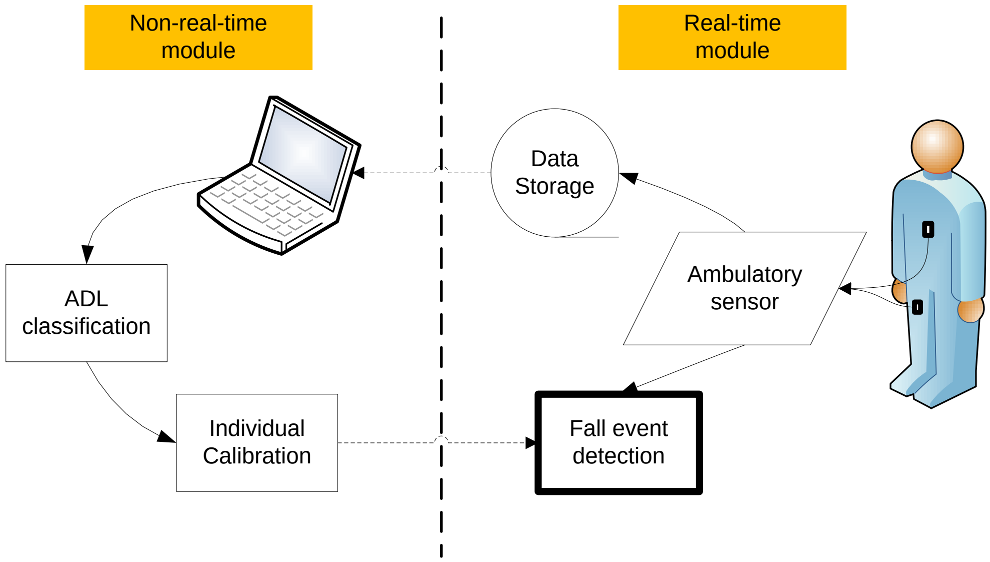

Figure 2 - Illustration of the integrative ambulatory measurement (IAM) framework

One important way to improve the fall detection performance is to employ an individualized detection threshold. To obtain such individual-specific information automatically, regular ADLs have to be recognized. This function is allocated to the non-real-time module. While the real-time module is continuously active, the non-real-time module only operates discretely during certain time slots (i.e. nap-time). It is expected that there will be certain periods of nap-time for the real-time component to pause. In the fall event detection case, this nap-time could be at night when the users take off the device or a specifically assigned weekly or even monthly maintenance time. During the nap-time, the data measured during the up-time (i.e. day time) is retrieved and analyzed. An activity classification algorithm is implemented to extract the motion feature relevant to each identified motion. An individual calibration algorithm is implemented to obtain an individual-specific fall detection threshold. In the current study, the data processing took place in a local computer. The result, the individual-specific fall threshold in this case, was then fed back to update the detection criteria used in the real-time module.

In essence, as time elapses, the individual-specific motion feature information is accumulated, and utilizing the individual calibration algorithm, more refined detection threshold can be achieved. It is then expected that the fall detection performances of the device would be improved over time.

Besides improving the detection accuracy, the individual-specific fall threshold obtained from this framework is also expected to provide a more rapid response, and thus potentially allow more lead time for the other protective systems to be activated before the impact. Together with other assistive devices (such as an air bag), this could directly reduce the physical injury associated with fall accidents.

It should be emphasized that the fall event application is just a specific scenario for which the IAM framework may be well suitable. This framework by itself dictates neither the choice of specific computation algorithms nor the specific hardware configurations (e.g. types of ambulatory sensors, communication protocols, computing platforms, etc). With such flexibility, the IAM framework may be able to accommodate different application scenarios which will specify the hardware and software aspects suitable for that application.

3.2. ADL classification (non-real-time module)

ADL classification is a prerequisite for the individual calibration function and is allocated in the non-real-time module within the IAM framework. Because the focus of the current study was to develop and evaluate the new fall detection algorithm and the individual calibration algorithm, a simple ADL classification scheme was adapted from the literature (Bussmann et al., 1998; Lyons et al., 2005), and a standardized ADL testing protocol was used.

The general principle of this ADL classification algorithm is to first detect the body postures during static phases and then to recognize the types of the dynamic activities between the postures using a rule-based approach. The types of the dynamic activities can include various postural transitions, gait activities and other motions.

Specifically, accelerometer signals from two IMUs (Inertial Measurement Units) were used in ADL classification. One IMU was placed on the frontal side of the thigh segment, and the other close to the sternum on the chest (Figure 2). The measurements represented the linear acceleration of thigh and trunk segments.

The schematic illustration of the ADL classification is shown in Figure 3. The entire processing was divided into four stages.

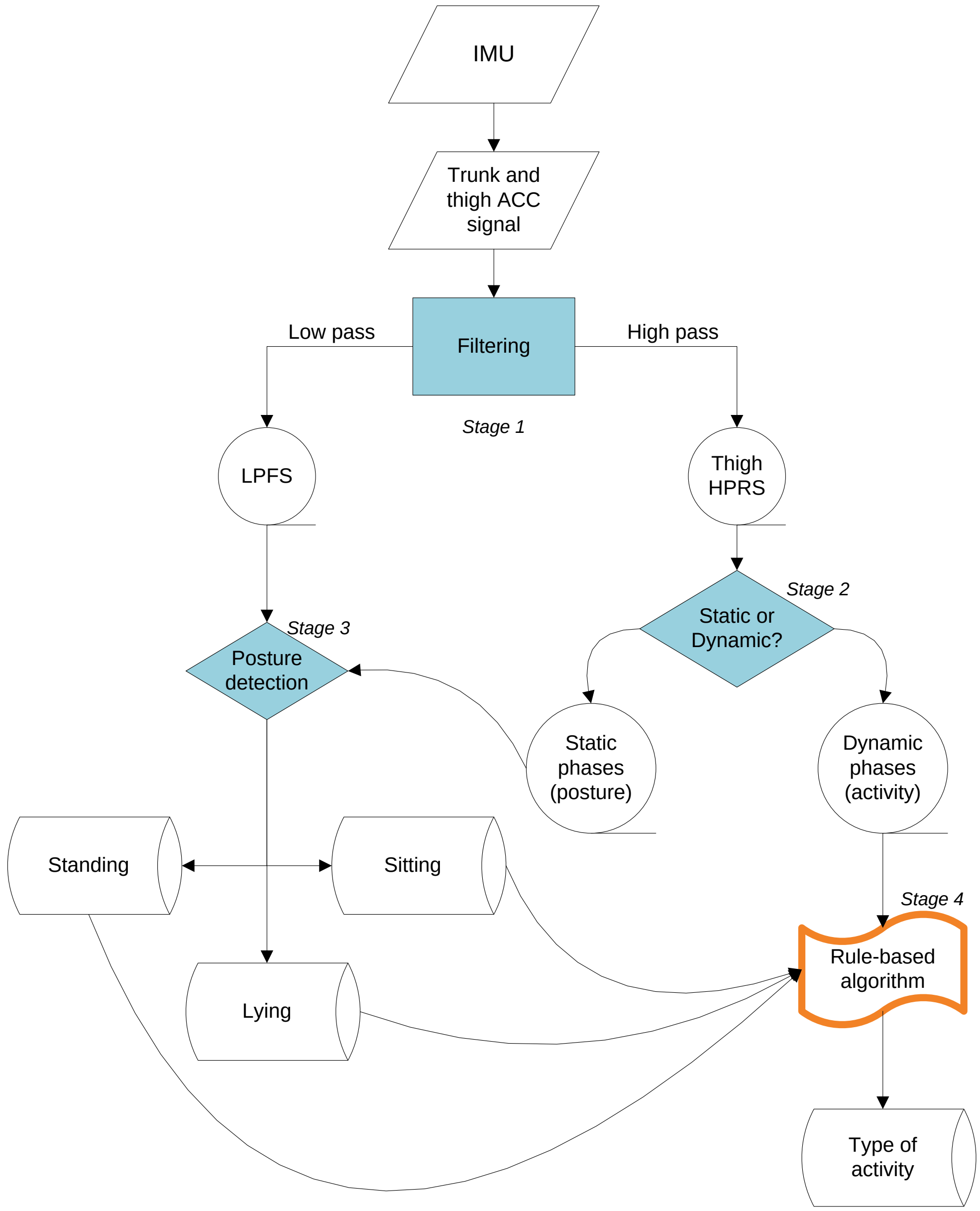

Figure 3 – Illustration of ADL classification scheme

3.2.1. Stage 1 - Filtering

Both the trunk and thigh accelerometer signals were first low-pass filtered (Butterworth, 4th order, 0.5Hz). The resulting signal (LPFS) was used in posture detection. The thigh accelerometer signal was further high-pass filtered, rectified and smoothed (Bussmann, Tulen, et al., 1998). The resulting signal (HPRS) was used to differentiate dynamic and static phases using the threshold technique.

3.2.2. *Stage 2 - Static or dynamic phases*

Differentiation between static (posture) and dynamic phases (postural transition and activity) was achieved by applying the threshold technique to the thigh HPRS signal. The rationale was that the more 'dynamic' a motion is, the more 'variable' the accelerometer signal will be, and it will contain more high frequency components (Bussmann, Tulen, et al., 1998). The threshold was empirically determined to be 0.04g from the data collected in this dissertation (Study 2). The entire thigh HPRS signal was segmented by this threshold into multiple static and dynamic phases.

3.2.3. *Stage 3 – Posture detection*

Posture detection was performed in static phases identified by stage 2. The thigh and chest LPFS signals were used to estimate the orientation of the thigh and trunk segments, respectively, using Eq. 1 (Williamson & Andrews, 2001).

$$\theta = tan^{-1}(\frac{a_z}{a_x})$$

Eq. 1

where a_z is the accelerometer signal in the longitudinal direction and a_x is the signal in frontal direction. The combination of the thigh and trunk segment orientations was used to identify the posture using a best-estimate approach (Lyons, et al., 2005). Because the reference values for healthy elderly population are not available in the literature, the orientation thresholds (Table 2) were empirically determined from the data collected in this dissertation (Study 2).

Table 2 - Orientation threshold for posture detection

Segment	Posture					
	Sitting		Standing		Lying	
	Range	Reference	Range	Reference	Range	Reference
Trunk	±60°	Vertical	±20°	Vertical	-30° ~ 45°	Horizontal
Thigh	±60°	Horizontal	±30°	Vertical	±30°	Horizontal

3.2.4. *Stage 4 – Activity detection*

The types of dynamic motion (activity or postural transition) for each dynamic session were determined by the posture types of the adjacent static phases. A rule-based algorithm specifies all the possible transitions between postures (Figure 4). For example, an activity between the posture 'standing' and the posture 'sitting' is considered as the 'sitting down' activity. It should be noted that this rule-based scheme is not meant to be exhaustive and only considers those possible activities/activity transfers that are common for a typical older adult.

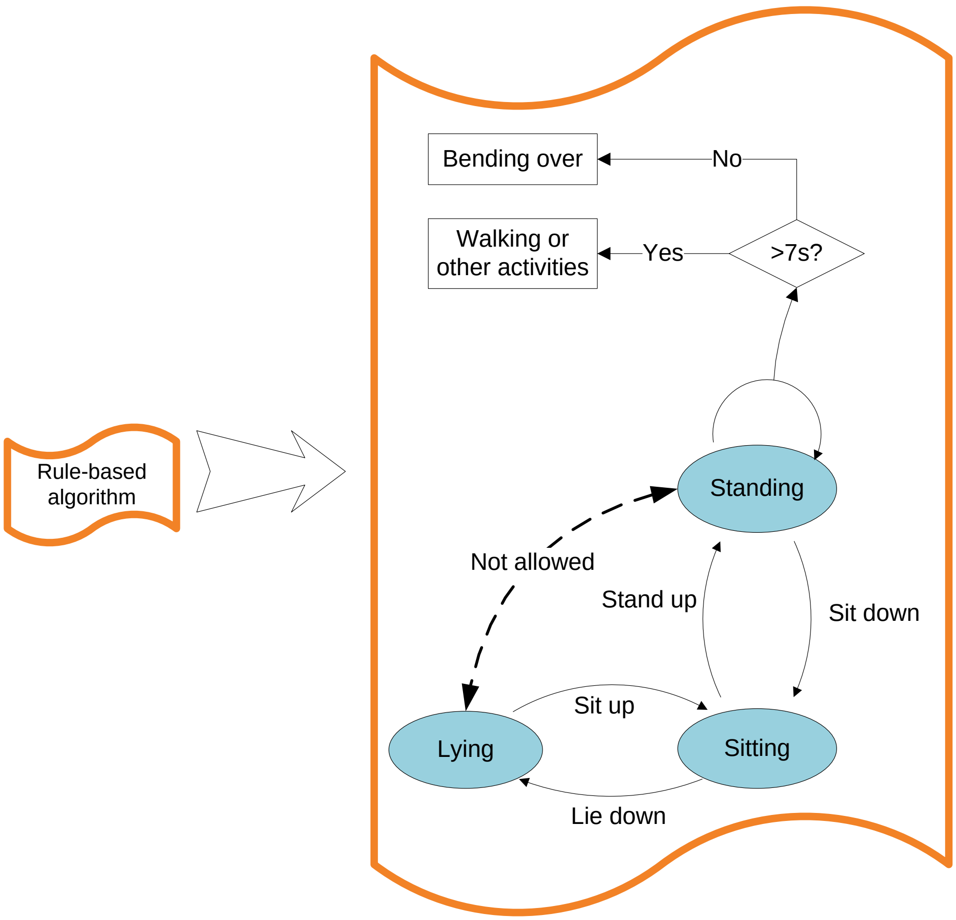

Figure 4 - Rule-based postural transition and activity detection

As with many other activity classification methods, several assumptions exist in this algorithm. It is assumed that activities except for postural transitions should always start with a standing posture. Meanwhile, there are only two categories of activities (bending over and other activities including walking), differentiated by the duration of the activity. For the purpose of fall event detection, the various types of postural transitions and bending over activities have been found to be the main sources of misdetection and false alarm (Nyan, Tay, Tan, et al., 2006). Therefore, as long as falls can be separated from non-fall activities (ADLs), detailed differentiation of ADLs involving walking is of less value for the proposed study. It may be argued that activities lasting less than 7s are not necessarily associated with bending over activity. For short-lasting activities, however, bending over is the most demanding activity that can be falsely detected as a fall. For individual calibration, it is sufficient to consider only the most demanding activity that is most relevant to fall detection. It is believed that categorizing short-lasting activities all together will not affect the individual calibration process; thereby it is a reasonable simplification for the current study. For example, suppose there are several trials of other short lasting activities like walking only two steps. These trials will get classified as bending over motions. The motion features from these trials will not be as high as those observed during bending over. Thus, the values from the individual calibration regarding the bending over activity will still be mainly influenced by the motion characteristics during bending. Therefore, gross categorization of short lasting activities is not expected to influence the performance of individual calibration process.

It should be noted that the IAM framework does not dictate the choice of a specific ADL classification algorithm. Choosing the current method to classify ADLs partly comes from the practical consideration of using as few sensors as possible, so as not to constrain the participants. As a matter of fact, a complex and sophisticated algorithm can be easily incorporated in future studies.

3.3. Automatic individual calibration (non-real-time mode)

The individual calibration function was designed to complement the fall detection process by updating the fall detection thresholds automatically. This function operated in the non-real-time module within the IAM framework.

Conceptually, the individual calibration is based on the relationship between fall detection threshold (*TH*) and two of the detection performance measures, sensitivity and specificity. For any threshold-based detection algorithm, the detection performance is dependent on the choice of a specific *TH*. With the changing TH, the sensitivity and specificity will move in opposite directions (Zweig & Campbell, 1993). As one increases, the other will decrease. For example, suppose an algorithm in which a fall is detected whenever the measurement is below a specific *TH*. Ideally, there might be cases when a fall detection algorithm is so effective that a single or a range of *TH* can achieve maximum (100%) sensitivity and specificity at the same time. In reality, however, sensitivity and specificity rarely reach their maximum simultaneously and an increase in *TH* will normally result in an increase in sensitivity but a decrease in specificity. Consequently, a compromise in performance measures has to be made in choosing a single or a range of *TH* for the algorithm. A generic or optimal

TH for a specific algorithm is usually determined in a way that the algorithm can reach desirable levels of sensitivity and specificity for a group of users. In terms of each individual user, however, an individualized *TH* instead of a generic *TH* is expected to achieve a better combination of sensitivity and specificity.

In practice, the individual calibration works in a way that it will gradually adapt the generic *TH* to a more individualized *TH* based on the user-specific motion characteristics during ADLs. Suppose an ADL monitor constantly records and classifies an individual's daily behavior over a period of time. Such a user-specific ADL dataset is sufficient to compute one of the fall detection performance measures: specificity. A user-specific *TH* can then be determined at a desirable level of specificity. Suppose an ADL monitor is worn for a prolonged time, a large ADL motion characteristic dataset will be available to compute a reliable and accurate *TH* which is individualized for that particular user. With this adapted *TH*, it is possible to achieve an optimal combination of sensitivity and specificity at an individual level.

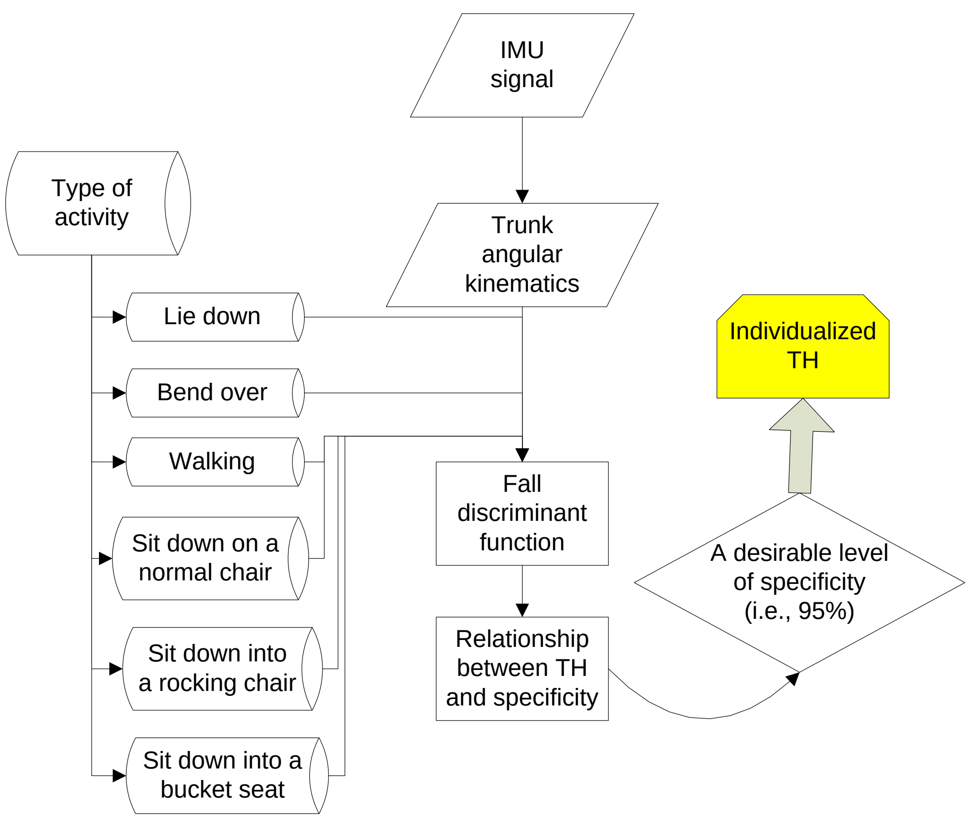

Figure 5 - Analysis scheme of individual calibration

Specific to the current study, an analysis scheme (Figure 5) was implemented. The trunk angular kinematics were analyzed. Due to the fall detection algorithm employed in the current study (see next section), only the trunk extension angle (α) and angular velocity (ω) were extracted and analyzed for each ADL activity. Trunk angular kinematics (α and ω) were directly measured by IMU on the sternum.

For any particular individual, the trunk angular kinematics (α and ω) were gathered for each repetition of the same motion. Predictive values were obtained by processing these measurements using the fall discriminant function. An activity ROC (ROC^a) curve was constructed for this individual using all the ADL trials (see chapter 4 for details). The minimum *TH* that could achieve a desirable level of specificity, which was 95% in the current study, was determined as the individualized *TH* for this individual. In case that 95% specificity was not possible, the *TH* corresponding to the highest specificity was used. In general, specificity was given higher priority over sensitivity in the current study in order to avoid false alarms

Such individualized *TH* has the following characteristics. First, it is individual specific. It is independent of the generic *TH* and is determined through analyzing an individual's ADL motion features. Such individualized *TH* is expected to facilitate the fall detection algorithm to minimize false alarms and misdetections.

Second, the individualized *TH* can also be updated periodically. There is no restriction on how many times or in what time interval the individual calibration process should be performed. As the recorded ADLs increases, the expanded motion feature database is expected to result in a more precise *TH*. Being able to update periodically the individualized *TH* may theoretically be used to monitor the ADL motion feature changes associated with aging or disease conditions. It should be noted that the optimal updating interval may influence the detection performance as well as the user compliance in practice, and will be investigated in future studies.

There are limitations associated with proposed individual calibration function. Most fundamentally, successful and accurate individual calibration is highly dependent on the accurate classification of common ADLs. However, because the ADL classification algorithm is functioning in a non-real-time manner, it is possible to implement a complex and sophisticated algorithm to improve the accuracy of ADL detection. Even with certain levels of ADL misdetection, it is expected that the effectiveness of fall detection using the individualized *TH* would not be worse than those using the generic *TH*.

3.4. Fall event detection (real-time mode)

A new fall event detection algorithm based on trunk angular kinematics is designed for detecting backward falling, which is the most common type of slip-induced fall accidents. This algorithm will be functioning in the real-time module within the IAM framework during the up-time.

The rationale is that people often execute voluntary activities (e.g. ADLs) in a controlled manner, as suggested by Wu (2000). This is reflected mainly in terms of motion intensity. For example, it has been shown that the horizontal and vertical velocities of body movement are within a well-controlled range during several common daily activities including sitting down, descending stairs, and transferring in/out of the tub (Wu, 2000). In other words, abrupt motion (with high speed or acceleration) may very likely be an involuntary activity such as falling. Such abrupt motions can be quantified by linear kinematics, angular kinematics or both. For example, the trunk linear velocity is increased dramatically during both forward and backward falling (Wu, 2000). This is also, explicitly or implicitly, the basis for various detection algorithms and sensors used by different investigators (Lindemann, et al., 2005; Nyan, Tay, Tan, et al., 2006). However, as found in these studies, motion intensity alone is not a sufficient criterion to differentiate between falling and ADLs. For example, Nyan et al. (Nyan, Tay, Tan, et al., 2006) utilized trunk backward angular velocity to detect fall events. Though a perfect sensitivity (100%) was demonstrated, several false alarms were raised during bending down and standing up. Subjects were found to generate similar backward trunk angular velocity occasionally during ADLs.

It is thus hypothesized that a new algorithm using motion intensity together with body posture may offer more accurate fall detection. The controlled way of executing a normal activity by an individual is not only reflected in the motion intensity, but also in controlling the posture during an activity. Controlling the posture during any activity is important for balance maintenance. Abnormally high motion intensity coupled with unsafe body posture may better characterize the involuntary, abrupt motions (i.e. falling).

In the new algorithm, two dimensions of motion features (trunk angle and trunk angular velocity) are used to detect the occurrence of falling. The choice of the second dimension, trunk angle, was based on the empirical observation that, during backward falls, abnormally high backward trunk angular velocity is always accompanied by a backward trunk orientation (Troy & Grabiner, 2006). On the contrary, the simultaneous presence of large backward trunk angular velocity and angle is rare in ADLs. On one hand, backward trunk rotation is rare for activities like standing up and bending down. On the other hand, though activities like lying down or even sitting are associated with substantial backward lean of the trunk, these activities are always under control with a slower rate of rotation. Therefore, it is expected that an algorithm incorporating both trunk angle and trunk angular velocity will offer substantial improvement in fall detection performance.

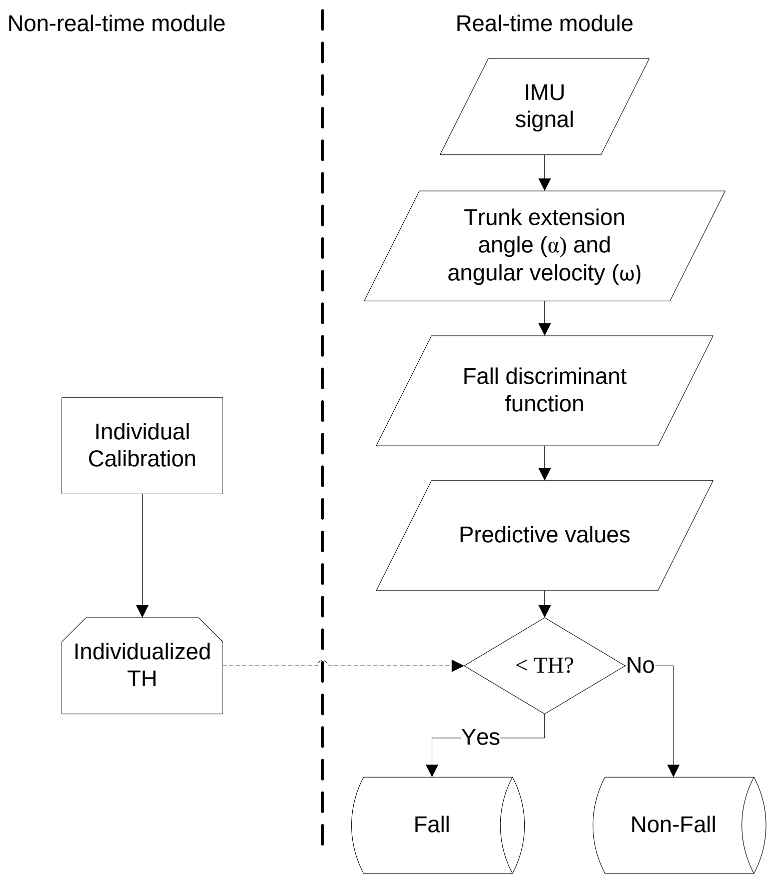

Figure 6 - Illustration of fall detection algorithm

Specific to the current study, the logical flow of the new fall detection algorithm is illustrated in Figure 6. During the up-time, both α and ω were continuously monitored. Fall discriminant function[1]

[1] The specific form of this function were derived via discriminative analysis in chapter 4&5.

was used to compute the predictive value for each pair of α and ω. These predictive values were then compared with either generic *TH* or individualized *TH* to determine the detection outcome.

Chapter 4

4. STUDY 1: TRUNK ANGULAR KINEMATICS DURING FALLS AND ADLS

4.1. Objectives and Hypotheses

Study 1 involved a biomechanical analysis of trunk motion characteristics during common ADLs and slip-induced backward falls using an optical motion analysis system. The objective of this study was to construct the new fall detection algorithm that could be used to differentiate falls from common ADLs utilizing a gold-standard assessment method. Specifically, it was hypothesized that backward fall motion characteristics (trunk angle and angular velocity) would be significantly different from common ADLs' trunk motion characteristics.

4.2. Participants

Ten elderly participants (> 65 years old) were recruited from the local community for this study (Table 3). They were required to be in generally good physical health. Potential participants were excluded from enrollment in the study, if they self-reported as having one or more of the exclusionary criteria (Appendix A) or they were deemed unsuitable by the study physician. A Medical History questionnaire was used as an initial screening tool (Appendix B). Informed Consent (Virginia Tech IRB #07-628) was approved by the IRB committee at Virginia Tech and obtained from the participants prior to any data collection.

Table 3 – Summary of participants' information

	Mean	SD
Age (years)	75	6
Weight (kg)	74.1	9.1
Height (cm)	174	7.5

The sample size required in this study was estimated based on the results obtained from a pilot study (see Appendix C). This pilot study simulated the performance of fall detection algorithms in differentiating slip-induced back falls from normal walking. The response time, as one of the primary performance measures in the proposed study, was used to calculate the power of the proposed experiment. In other words, the power of the test was determined by focusing on sample size large enough to detect differences in response time between using the new algorithm and using the baseline algorithm (Nyan, Tay, Tan, et al., 2006) with high probability (>0.80). The following formula (Eq. 2) was used to calculate the power (O'Brien & Lohr, 1984):

$$\text{Power} = \text{prob}(F > F_{crit,v_1,v_2,NC})$$

Eq. 2

where $v_1 = r - 1$, $v_2 = r(n\text{-}1)$, *r* is the number of groups, and *n* is the number of samples per group. *NC* is the non-centrality parameter, which represents the true difference of the variable of interest. *NC* can be determined by parameters including Δ, σ^2, and *n*. Δ indicates the difference of the variable between two adjacent groups. σ^2 is the mean square error.

It can be clearly seen that, in order to calculate the sample size *n* to achieve a desired level of power, the values of *r*, Δ, and σ^2 must be known. As this study will have two groups (the new algorithm and the baseline algorithm), *r* is equal to 2. As suggested by the pilot study, the difference between the group means and σ is expected to be approximately 200ms and 128ms (see Appendix C). Using this information, nine participants are needed to achieve a power of 0.84 with the Type I error less than 0.05. In order to utilize the Latin square design (order = 5) in the ADL testing, the sample size of the current study was set to be 10.

4.3. Apparatus and Procedures

4.3.1. For normal walking and slip-induced backward falls

A detailed description of the experiment protocol has been published previously (Liu & Lockhart, 2005). Briefly, participants were instructed to walk at a normal pace on a linear walkway (1.5m×15.5m) with the protection of an overhead harness system. Unexpected slips were induced by changing the dry floor surface into slippery surface (covered with 3:1 KY-Jelly and water mixture) without participants' awareness. Two force-plates (BERTEC # K80102, Type 4550-08, Bertec Corporation, OH 43212, USA) and a six-camera ProReflex system (Qualysis, Sweden) were synchronized to collect kinetic and kinematics at a sampling rate of 100Hz. A biomechanical model (Lockhart, Woldstad, & Smith, 2003) using 27 marker-set was adapted in the current study. One additional marker was placed close to the sternum.

Given the slip perturbation, participants' reactions may be classified into either recovery or fall. Fall was identified as the trial in which the participant had to rely on external assistances (i.e. overhead harness) other than floor support to regain their balance. Quantitatively, falls were considered as those trials in which the participant's vertical shoulder position (as measured by the shoulder marker) dropped more than 20 cm[2] from normal shoulder height after a slip. All other trials were considered as recovery trials.

The slippery surface was introduced repeatedly until three slip perturbation trials were obtained from each participant. After each trial with the slippery surface, participants were encouraged to walk continuously as normal as possible at a normal pace for 5 to 10 minutes before the next slippery trial. The participants had no knowledge regarding the exact timing of the floor surface change.

4.3.2. For ADLs

A six-camera optical motion analysis system (ProReflex, Qualysis, Sweden) was used to collect the kinematics data at a sampling rate of 100Hz. The same biomechanical model (Lockhart, et al., 2003) using a 27 marker-set was adopted in this study. A gait analysis laboratory (Locomotion Research Lab, Virginia Tech) with regular living furniture (bed, chair, desk, etc) was used as the experimental setting.

Participants were first required to change into experimental clothing (short and sleeveless shirt). This was to facilitate the attachment of the reflective markers and to minimize the possible interference of the clothing to the data measurement.

Each participant was then instructed to perform the following 5 types of daily activities (Table 4). For the sitting down activity (SN, Figure 7-a), the participant was asked to sit onto a regular office chair which is about the knee height (individual adjusted), wait 1 or 2 seconds, and then stand up. For the sitting in to a rocking chair activity (SR, Figure 7-c), after sitting down, the participant was free to move his/her body in a relaxed way as allowed by the rocking chair. For the sitting into a bucket seat activity (SB, Figure 7-b), the participant sat into a chair about half of the knee height to mimic the sitting motion of getting into a car. For the lying down activity (LD, Figure 7-e), the participant lied down on his/her back from a sitting posture on a medical bed. For the bending over activity (BD,

[2] During the experiment setup, the overhead harness was individually adjusted so that the trunk segment could only drop 20 cm vertically without being stopped by the harness.

Figure 7-d), the participant bent over from a standing posture to pick up an object (e.g., a roll of duck tape), which was approximately one foot in front of the participant, from the floor.

Table 4 – Summary of walking activities and ADL activities

Session	Code	Description
Walking	F	Slip-induced backward fall
	W	Walking at a normal speed
ADL	SN	Sit into a normal chair, then stand up
	SR	Sit into a rocking chair, then stand up
	SB	Sit into a bucket seat, then stand up
	LD	Lie down from a sitting posture, then rise up
	BD	Bend over from a standing posture and rise up

Before data collection, each participant was allowed approximately 10 minutes to get familiar with the furniture and to practice the activities. During data collection, participants were first asked to "stand straight and stand quietly for 5 seconds to collect base-line data. Afterwards, participants were instructed to perform these ADLs as naturally as possible at their own pace. At the beginning and the end of each trial, they were required to maintain the static posture for 1 second. No other instructions were given. All the timing information was provided to the participants via auditory cues by the experimenter.

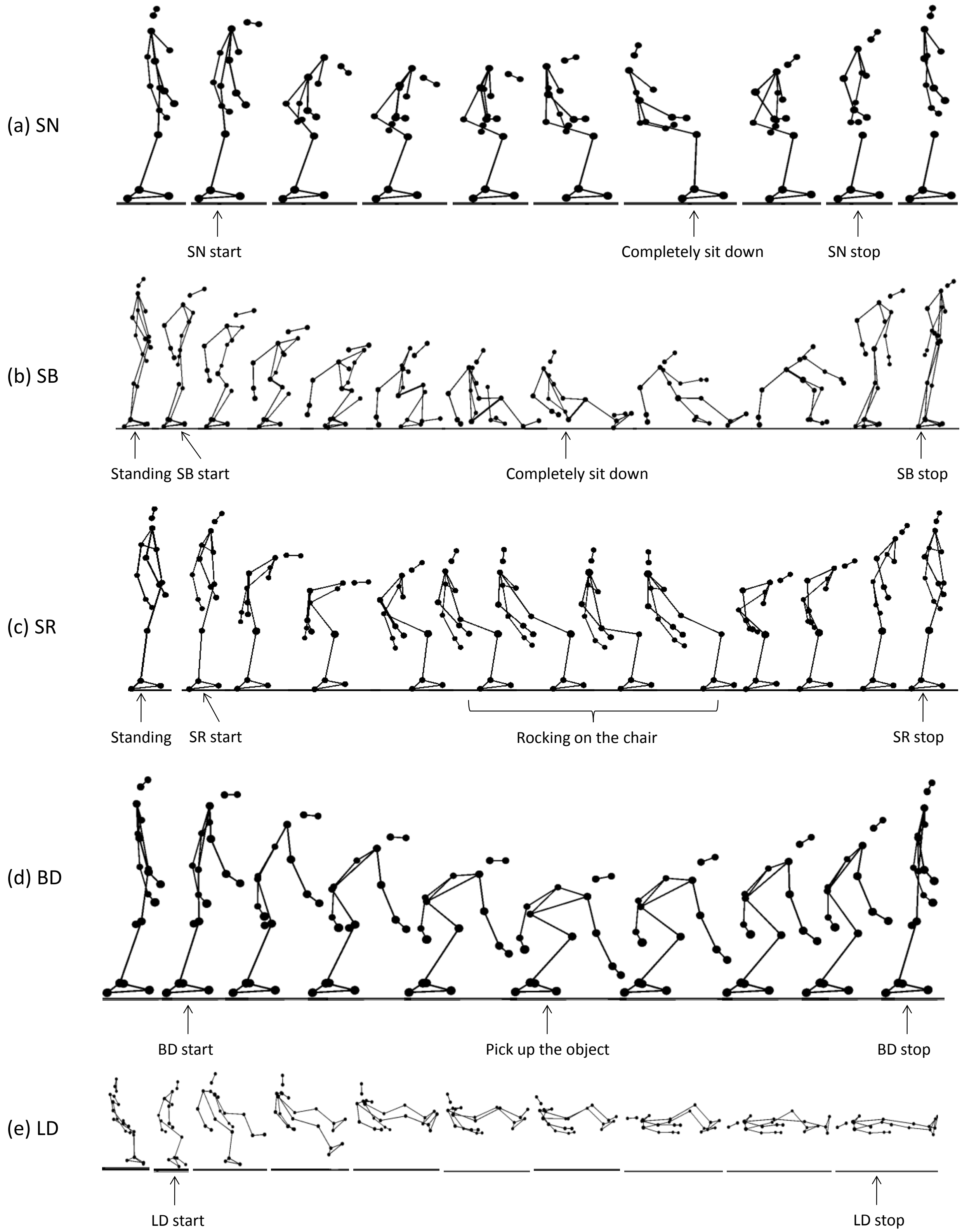

Figure 7 – Illustration of ADLs: (a) sitting on a normal chair; (b) sitting on a rocking chair; (c) sitting into a bucket seat; (d) bending over; (e) lying down

4.3.3. Presentation order of walking session and ADL session

The entire experiment was divided into a walking session and an ADL session. Within the walking session, normal walking trials were measured prior to slip-induced falls. Within the ADL session, the 5 ADLs (Table 4) were performed according to the order specified by a balanced Latin square table of order 5 (Table 5) in order to control the carry-over effect. This table was manually generated according to the rules specified in the literature (Williges, 2006).

Table 5 – Presentation order of ADL activities (Balanced Latin square of order 5)

		Subject No.									
		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Presentation order	1	SN	SR	SB	LD	BD	SN	SR	SB	LD	BD
	2	SR	SB	LD	BD	SN	SR	SB	LD	BD	SN
	3	BD	SN	SR	SB	LD	BD	SN	SR	SB	LD
	4	SB	LD	BD	SN	SR	SB	LD	BD	SN	SR
	5	LD	BD	SN	SR	SB	LD	BD	SN	SR	SB

Data acquisition was performed by a custom-designed program in Labview (Labview 8.2, National Instruments, TX).

4.4. Data Reduction

Kinematics data from the motion analysis system was low-pass filtered using a zero-phase 4th order Butterworth filter with a cut-off frequency of 6Hz. The trunk sagittal angle and angular velocity was calculated using the kinematics data of reflective markers placed on the acromions and sternum. The trunk angles were reported with the vertical direction being the reference of zero.

To facilitate the description of the fall dynamics, the following events were defined (see Figure 8-b):

- Fall initiation: an event same as the definition of slip start (for details, see Lockhart, et al., 2003) when the forward heel velocity occurs after heel contact.

- Fall completion: the event when the trunk COM reaches its lowest vertical position.

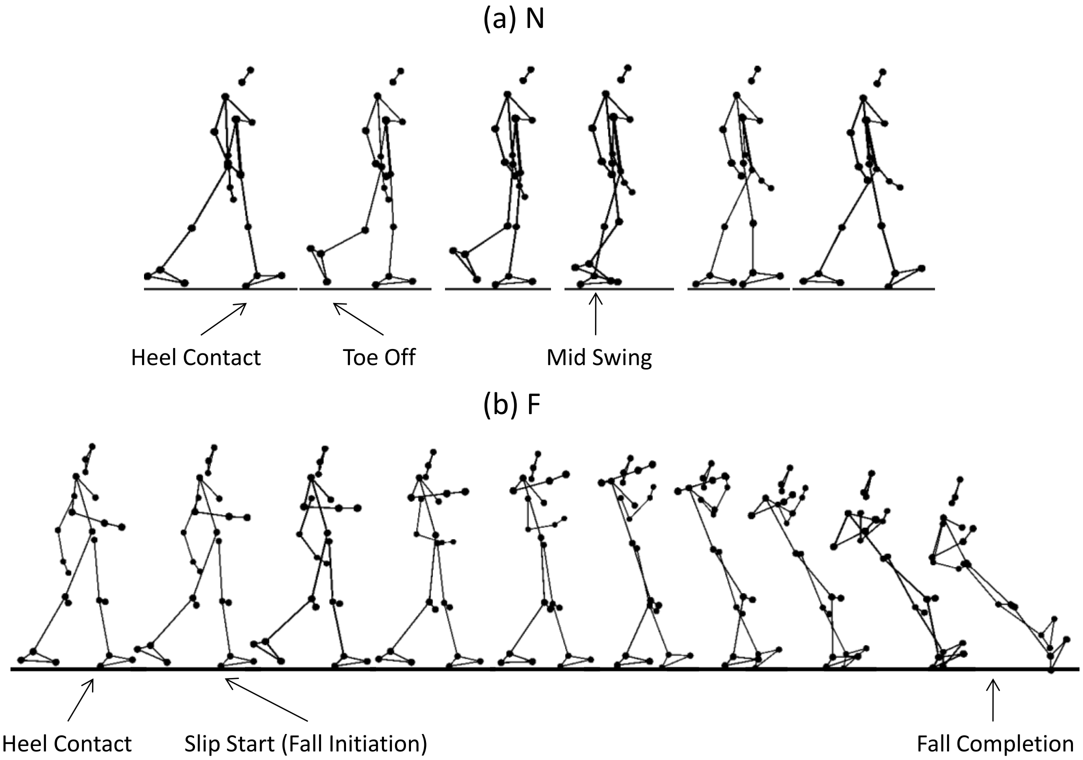

Figure 8 –Illustration of normal walking (a) and slip-induced backward falls (b). Note that because of the protective harness, the participants were not completely on the ground.

To facilitate the description of the ADL activity, the start and end point of each trial of activity were determined as the following. First, the mean and SD (standard deviation) of trunk angular velocity during the initial 1 second of each trial of activity were analyzed. Then, the start point of an activity was defined as whenever the trunk angular velocity deviates over 2 SD from the mean during the initial 1 second (Giansanti & Maccioni, 2006). Similarly, the end point for that activity was defined as whenever the trunk angular velocity deviated more than 2 SD from the mean during the last 1 second.

Phase plots of trunk angular kinematics were generated with trunk angle as the X axis and trunk angular velocity as the Y axis for each activity. During normal walking, the phase plots were generated during one stance phase. During falling, the phase plots were generated from fall initiation to fall completion. During ADLs, the phase plots were generated between the activity start and end points.

All of the data analyses were performed using a custom-designed MATLAB program (MATLAB R2007b, MathWorks, USA).

4.5. Discriminant Analysis

Predictive discriminant analysis (Seber, 1984) was performed to determine whether and how well the trunk angular kinematics could distinguish backward falls from ADLs. Two algorithms, the new (proposed) algorithm (algorithm I) utilizing both trunk sagittal angle (α) and trunk sagittal angular velocity (ω), and the baseline algorithm (algorithm II, $F_{AlgorithmII}(\omega)$) utilizing only angular velocity, were evaluated with the data collected in this study. Since the new algorithm was based on two-dimensional information, both linear (algorithm I-L, $F_{AlgorithmI\text{-}L}(a, \omega)$) and quadratic (algorithm I-Q, $F_{AlgorithmI\text{-}Q}(a, \omega)$) forms of discriminant functions were evaluated. Thus, three discriminant functions (algorithm I-L, algorithm I-Q, and algorithm II) were constructed and evaluated in this study.

For the discriminant analysis, the data from all the activities, including ADLs and falls, were pooled together and prepared in such a way that each pair of data points ((α, ω) as in algorithm I) or each data point (ω as in algorithm II) was associated with a group variable indicating either fall (F) or non-fall (NF) (see Table 6 for examples).

Table 6 – Sample data for instantaneous ROC plot (ROC^i)

Activity	Trunk angle (α)	Trunk angular velocity (ω)	Group
…	...	…	…
SN	3.5°	50.1°/s	Non-Fall
…	…	…	…
LD	-70.1°	-61.2°/s	Non-Fall
…	…	…	…
F	-2.8°	-150.5°/s	Fall

Receiver Operating Characteristic (ROC) curves (Zweig & Campbell, 1993) were used to quantify the overall performance of algorithm I and II. Two types of ROC curves were designed and implemented in this study. One was termed *instantaneous* ROC (ROC^i). The detection outcome used in making ROC^i was determined according to the following rule (also see Table 7):

- Within each ADL trial (including normal walking), at a specific instant, if the associated pair of data points (as in algorithm I) or the associated data point (as in algorithm II) was classified as Fall instead of Non-Fall, the detection outcome for this particular instant was considered as false positive (FP). Otherwise, this particular instant was considered as true negative (TN).

- Within each fall trial, at a specific instant, if the associated pair of data points (as in algorithm I) or the associated data point (as in algorithm II) was classified as Fall instead of Non-Fall, the detection outcome for this particular instant was considered as true positive (TP). Otherwise, this particular instant was considered as false negative (TN).

Table 7 – Rule of detection outcome in ROC^{i}

		Detection of each instant	
		as Fall	as Non-Fall
Nature of each instant	Fall	true positive (TP)	false negative (FN)
	Non-Fall	false positive (FP)	true negative (TN)

The other type of ROC plot was termed *activity* ROC (ROC^{a}), which used the same data set but reported the detection performance on the activity level based on the following rule (also see Table 8):

- For each ADL trial (including normal walking), if any pair of data points (as in algorithm I) or any data point (as in algorithm II) was classified as Fall instead of Non-Fall, the detection outcome for this particular trial was considered as FP. Otherwise, this particular trial was considered as TN.

- For each fall trial, if any pair of data points (as in algorithm I) or any data point (as in algorithm II) was classified as Fall instead of Non-Fall, the detection outcome for this particular trial was considered as TP. Otherwise, this particular trial was considered as FN.

Table 8 - Rule of detection outcome in ROC^{a}

		Detection of each activity trial	
		as Fall	as Non-Fall
Nature of each activity trial	Fall	true positive (TP)	false negative (FN)
	Non-Fall	false positive (FP)	true negative (TN)

ROC^{i} reported the detection performance at each instant for all the activities (including falls), and represented the overall performance (sensitivity and specificity) of fall detection algorithm in detecting each instantaneous moment into Fall or Non-Fall cases. ROC^{i} was useful in constructing the discriminant function in discriminant analysis. In contrast, ROC^{a} reported the detection outcome at the activity level and represented the performance of the fall detection algorithm in detecting each activity as a whole into Fall or Non-Fall cases. ROC^{a} was considered as a faithful performance index for fall event detections.

In order to make ROC^{i} and ROC^{a}, two performance measures (sensitivity and specificity) were defined according to the following equations:

$$Sensitivity = \frac{TP}{TP+FN} \times 100\%$$

Eq. 3

Sensitivity was used to quantify the rate of the number of correctly detected falls relative to the number of actual falls. The opposite aspect of sensitivity is the rate of misdetection (misdetection + sensitivity = 100%). The higher the sensitivity is, or the lower the rate of misdetection is, the better the detection performance will be.

$$Specificity = \frac{TN}{TN+FP} \times 100\%$$

Eq. 4

Specificity was used to quantify the rate of the number of correctly detected ADLs relative to the number of ADLs. The opposite aspect of specificity is the rate of false alarm (false alarm + specificity = 100%). The higher the specificity is, or the lower the rate of false alarm is, the better the detection performance will be.

Discriminant function and ROC^{a} curves were constructed in MATLAB (MATLAB R2007b, MathWorks, USA). ROC^{i} curves and the related discriminant analyses were performed in JMP 7.0 (SAS Institute, USA). A significance level of $p \leq 0.05$ was used.

4.6. Results

4.6.1. Trunk angular kinematics during normal walking

The gait parameters during normal walking are summarized in Table 9. As shown in Figure 9-a, individuals always walked with a slight trunk flexion (mean = 5.6 ° / SD = 2.9 °) during normal walking, with peak flexion and peak extension occurring approximately at heel contact and toe off, respectively. The trunk angular velocity profile was characterized by two extension velocity peaks occurring at about 10% and 90% of stance phase, and one flexion velocity peak at about 50% of stance phase (Figure 9-b). The peak trunk sagittal angular velocity had a limited range from 7 °/s in flexion to 9.5 °/s in extension (Table 11). The phase plots of trunk sagittal angular kinematics exhibited a repetitive and elliptical pattern, which occurred within the 2nd and 3rd quadrants of the phase plot diagram (Figure 9-c).

Table 9 - Gait parameters during normal walking

	Mean	SD
Walking velocity (mm/s)	1295.8	148.3
Step length (mm)	711.6	77.1
Stance time (ms)	67.2	6.2
Stride time (ms)	108.3	9.1
RCOF[1]	-0.16	0.02
HCV[2] (mm/s)	900.2	293.3

[1]: Required Coefficient of Friction / [2]: Heel Contact Velocity

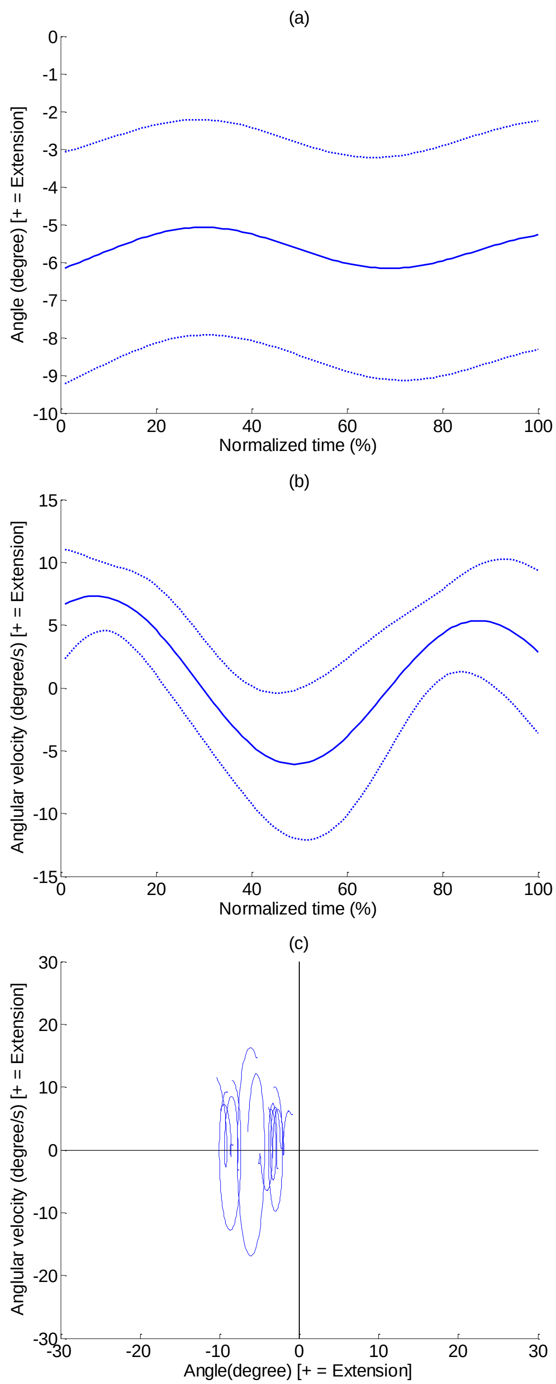

Figure 9 – Trunk angular kinematics during normal walking; (a) and (b) ensemble average profiles (dash line represents ±1SD) during stance time, with 0% and 100% indicating heel contact and toe off, respectively; (c) composite illustration of phase plots from all the participants during stance phase

4.6.2. Trunk angular kinematics during slip-induced backward fall

Totally, 30 perturbation trials were collected, including 13 backward falls, 15 successful recovery trials, 1 forward fall, and 1 sideway fall. For the purpose of the current study, only the 13 backward fall trials were analyzed.

The gait parameters associated with slip-induced backward falls are summarized in Table 10. As illustrated in Figure 10-a and Figure 10-b, backward falls were characterized by a simultaneous rapid increase of both trunk extension angle and trunk extension angular velocity, with peak angle and angular velocity reaching, on average, 11 ° and 139.7 °/s (Table 11), respectively. The corresponding phase plot exhibited a characteristic parabola shape (Figure 10-c), which was clearly distinguishable from those elliptical pattern observed previously during normal walking (Figure 9). Starting from slip initiation until slip end, the trunk phase plot followed a similar pattern as observed in normal walking, in which trunk extension increased slightly while trunk extension angular velocity decreased. After the slip end, however, the trunk extension angular velocity started to increase rapidly, together with increasing trunk extension. The trajectories from slip end to fall completion were mainly located within a narrow band of 1st and 2nd quadrants on the phase plot diagram.

Table 10 - Gait parameters during slip-induced backward falls

	Mean	SD
RCOF*	-0.10	0.03
HCV (mm/s)	908.2	554.7
SD1 (mm)	202.5	222.7
SD2 (mm)	364.8	282.4
PSHV (mm/s)	2611.2	998.7

*RCOF: Required Coefficient of Friction; HCV: Heel Contact Velocity; SD1: Slip Distance 1; SD2: Slip Distance 2; PSHV: Peak Sliding Heel Velocity

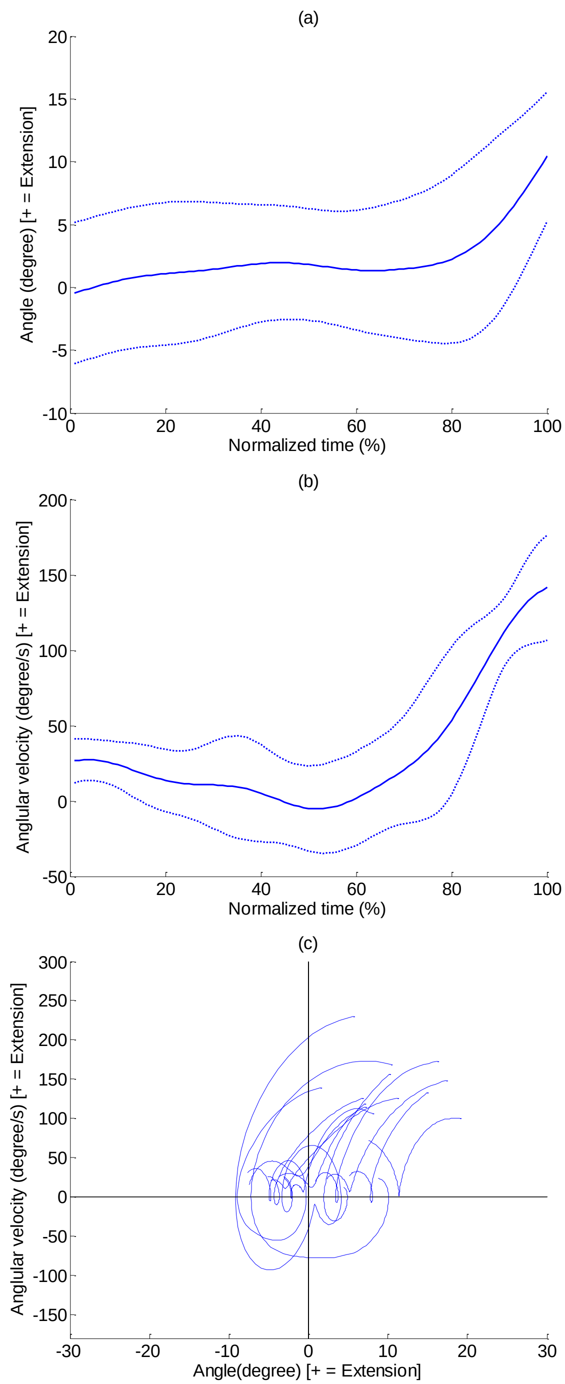

Figure 10 – Trunk angular kinematics during slip-induced backward falls; (a) and (b) ensemble average profiles (dash line represents ±1SD) from heel contact (0%) to fall end (100%); (c) composite illustration of phase plots during backward falls

4.6.3. Trunk angular kinematics during bending over and rising up (BD)

The bending over activity can be divided into two phases: an initial phase characterized by trunk flexion angular velocity and increasing trunk flexion, and a later phase characterized by trunk extension angular velocity and decreasing trunk flexion (Figure 11-a, b). The trunk flexion peaked approximately at the middle of the activity (Figure 11-a), with an average of 82.4 °. The peak trunk flexion and extension angular velocities were comparable, with an average of 131.6 °/s and 118.7 °/s, respectively (Table 11). It should be noted that bending over activity had the highest trunk flexion and flexion velocity among all the activities in the current study and the second highest trunk extension velocity, next to backward falls (Figure 17). Trunk phase plot during bending over (Figure 11-c) also featured an elliptical pattern, located entirely within the 2nd and 3rd quadrants of the phase plot diagram.

4.6.4. Trunk angular kinematics during lying down (LD)

The trunk angular kinematics during lying down were characterized by a dramatically increasing trunk extension (Figure 12-a) and an extension-dominant angular velocity (Figure 12-b). The peak trunk extension occurred at the end of lying down, with an average of 142.7 °, while the peak extension velocity reached an average of 90 °/s. It should be noted that lying down activity had the highest trunk extension angle among all the activities in the current study and the third highest extension velocity, next to backward falls and bending over (Figure 17). Distinctive from those of other ADLs in this study, the trunk angular phase plot of lying down (Figure 12-c) was characterized by a flattened, parabolic pattern, which was mainly located within the 1st quadrant of the phase plot diagram.

4.6.5. Trunk angular kinematics during sitting down (SN)

Similar to that of bending over, the trunk angular kinematics of the sitting down activity can be divided into two phases: an initial phase characterized by trunk flexion angular velocity and increasing trunk flexion angle, and a later phase characterized by extension angular velocity and decreasing flexion angles (Figure 13-a, b). Compared to bending over, however, sitting down was characterized by lower average peak flexion (53.6 °/s), lower average peak flexion velocity (85.4 °/s), and lower extension velocity (84.7 °/s) (Table 11). Similar elliptical pattern as observed during BD can also be observed in the angular phase plot of sitting down (Figure 13-c). The majority of the trunk kinematics was also located within the 2nd and 3rd quadrants of the phase plot diagram.

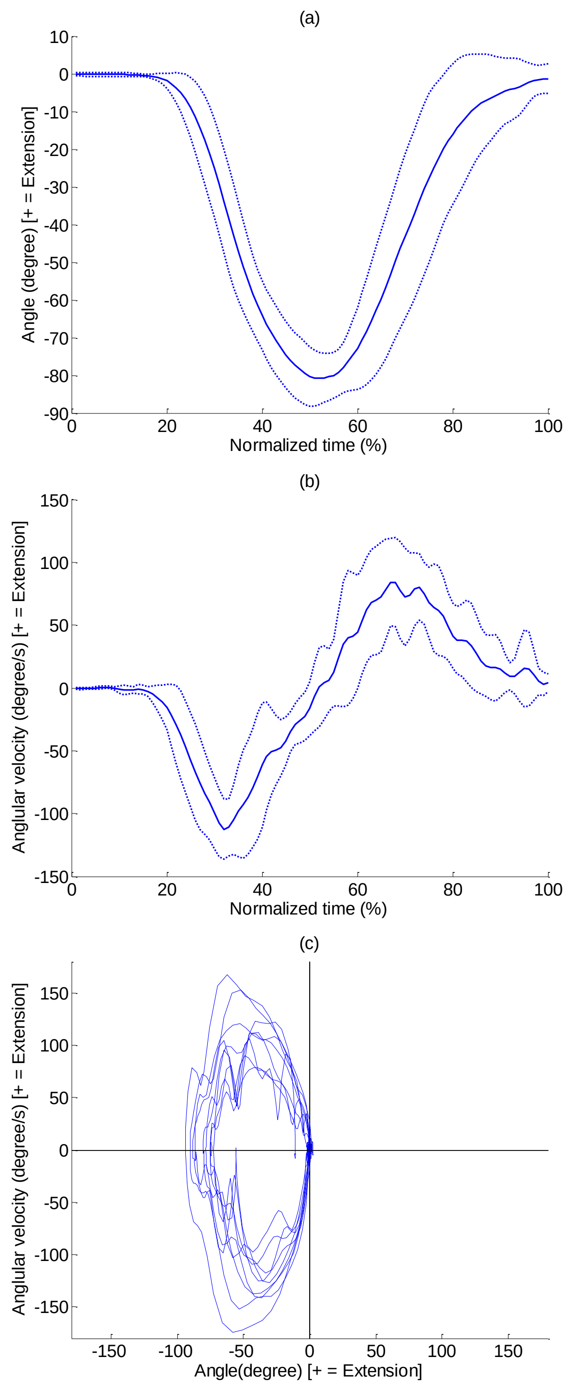

Figure 11 – Trunk angular kinematics during bending over (BD); (a) and (b) ensemble average profiles (dash line represents ±1SD); (c) composite illustration of phase plots from all the participants

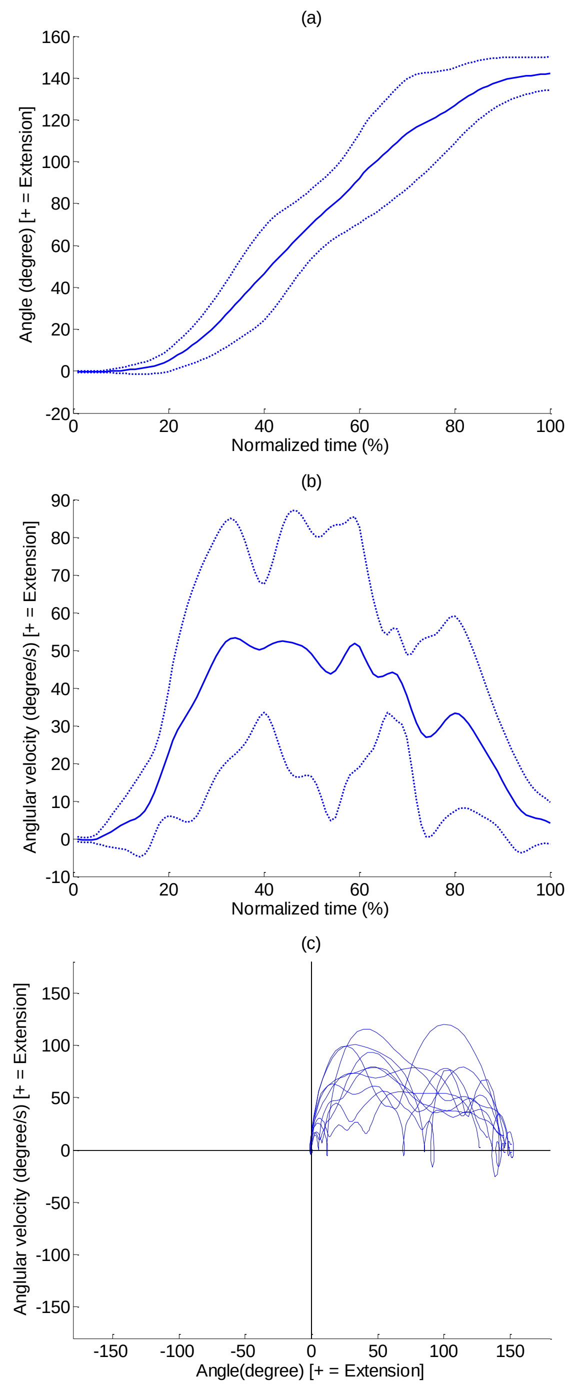

Figure 12 - Trunk angular kinematics during lying down (LD); (a) and (b) ensemble average profiles (dash line represents ±1SD); (c) composite illustration of phase plots from all the participants

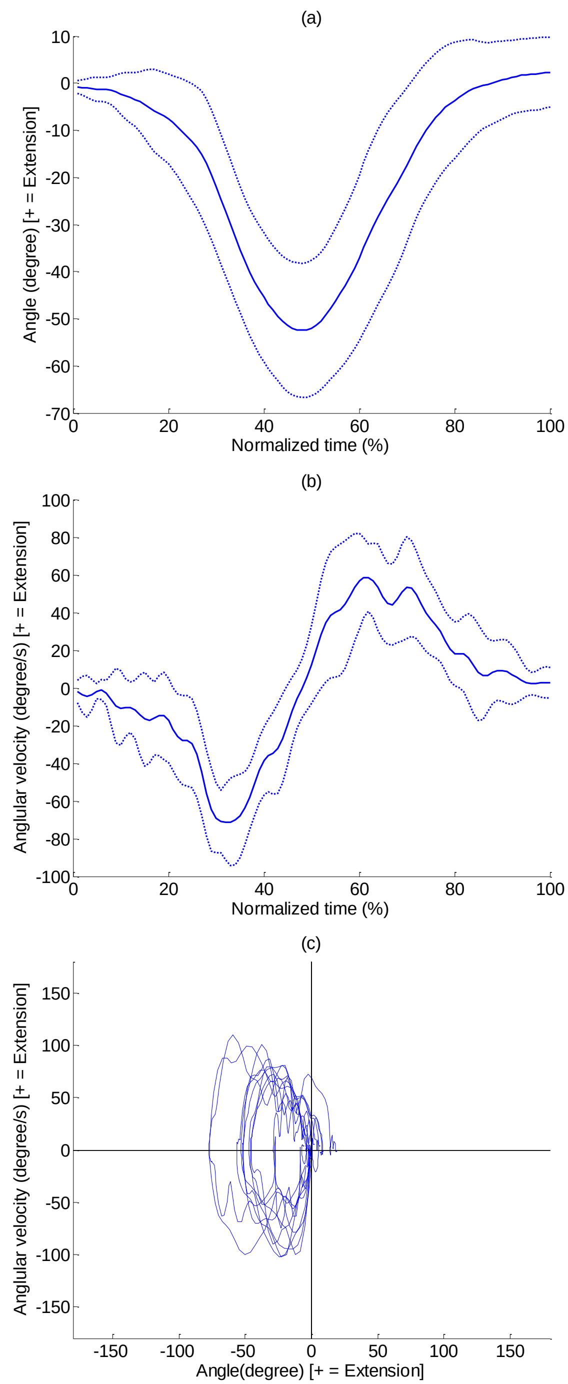

Figure 13 – Trunk angular kinematics during sitting down (SN); (a) and (b) ensemble average profiles (dash line represents ±1SD); (c) composite illustration of phase plots from all the participants

4.6.6. Trunk angular kinematics during sitting into a rocking chair (SR)

The activity of sitting into a rocking chair was analyzed from the start of sitting down to the end of standing up. As illustrated in Figure 14-a and Figure 14-b, no distinguishable pattern of the trunk angular kinematics can be observed during sitting into a rocking chair. Sitting into a rocking chair was dominated by a trunk flexion angle, as the average peak flexion (56.5 °) was considerably greater than the average peak extension angle (14.3 °) (Table 11). Compared to those during sitting down on a normal chair, the peak angular velocity were slightly higher during sitting into a rocking chair, with peak flexion velocity and peak extension velocity to be, in average, 96.7 °/s and 89.8 °/s, respectively (Table 11). As illustrated in the phase plot (Figure 14-c), the trunk kinematics during SR were mainly located in the 2nd and 3rd quadrants of the phase plot diagram.

4.6.7. Trunk angular kinematics during sitting into a bucket seat (SB)

Similar to bending over (Figure 11) and sitting down on a normal chair (Figure 13), sitting into a bucket seat was also characterized by an initial increasing and then decreasing trunk sagittal flexion angle (Figure 15-a). The trunk angular velocity during SB, however, was highly irregular (Figure 15-a), which was different from the smooth two phase pattern during SN and BD. With peak flexion angle, peak flexion velocity and extension velocity to be 73.1 °, 100.5 °/s and 112.1 °/s, respectively, the peak trunk angular kinematics were slightly higher than that of the other two types of sitting activities (SN and SR). With an irregular angular phase plot pattern (Figure 15-c), the trunk angular kinematics during SB were also mainly located within the 2nd and 3rd quadrants of the phase plot diagram.

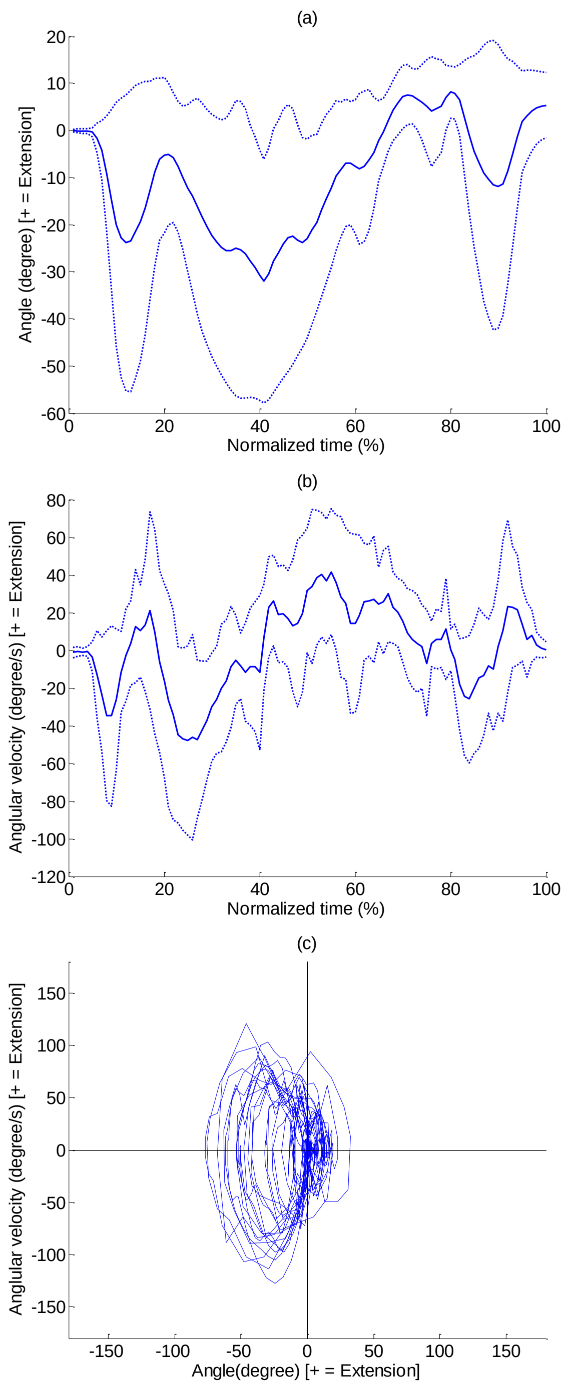

Figure 14 – Trunk angular kinematics during sitting into a rocking chair (SR); (a) and (b) ensemble average profiles (dash line represents ±1SD); (c) composite illustration of phase plots from all the participants

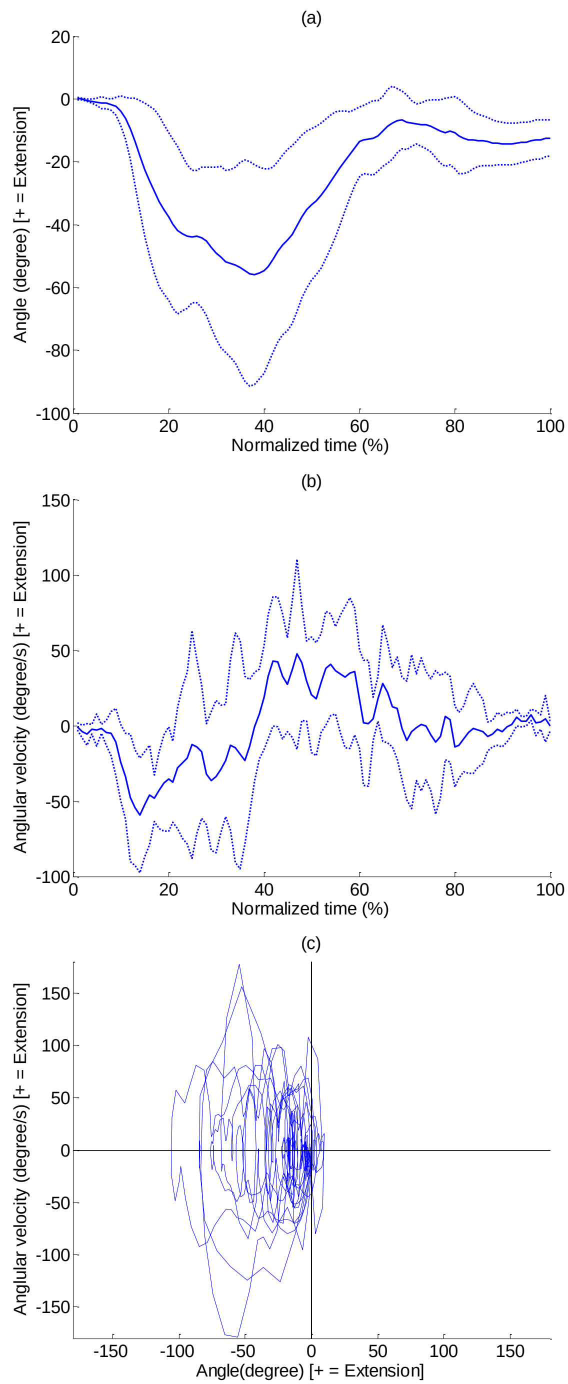

Figure 15 – Trunk angular kinematics during sitting into a bucket seat (SB); (a) and (b) ensemble average profiles (dash line represents ±1SD); (c) composite illustration of phase plots from all the participants

4.6.8. Comparison of trunk angular kinematics during ADLs and slip-induced backward falls

Ensemble average profiles of trunk angular kinematics were shown in Figure 16 for all the ADLs and backward falls. Peak trunk sagittal angular kinematics were summarized in Table 11 and contrasted in Figure 17.

In terms of trunk sagittal angles, three types of sitting down (SN, SB and SR) and bending over were all flexion dominant, while lying down was clearly extension dominant. Compared to ADLs, trunk sagittal angular range of motion were limited for both normal walking and slip-induced backward falls. In terms of trunk sagittal angular velocity, the backward falls were distinguishable by an extremely high peak extension velocity at the end (Figure 16-b). The two ADLs that had peak extension velocities close to that during falls were bending over and sitting down into a bucket seat (Figure 17).

From the perspective of angular phase plot, the backward falls were clearly distinguishable from ADLs (Figure 16-c). The trunk angular kinematics of all the ADLs except lying down was mainly located within the 2^{nd} and 3^{rd} quadrants of the phase plot diagram. On the contrary, the trunk kinematics during backward falls was uniquely located in a narrow region close to the positive vertical axis and within the 1^{st} quadrant of the phase plot. Even though it was mainly located in the 1^{st} quadrant, the trunk kinematics during lying down was flattened towards the positive horizontal axis and thus separate from the region occupied by fall activities.

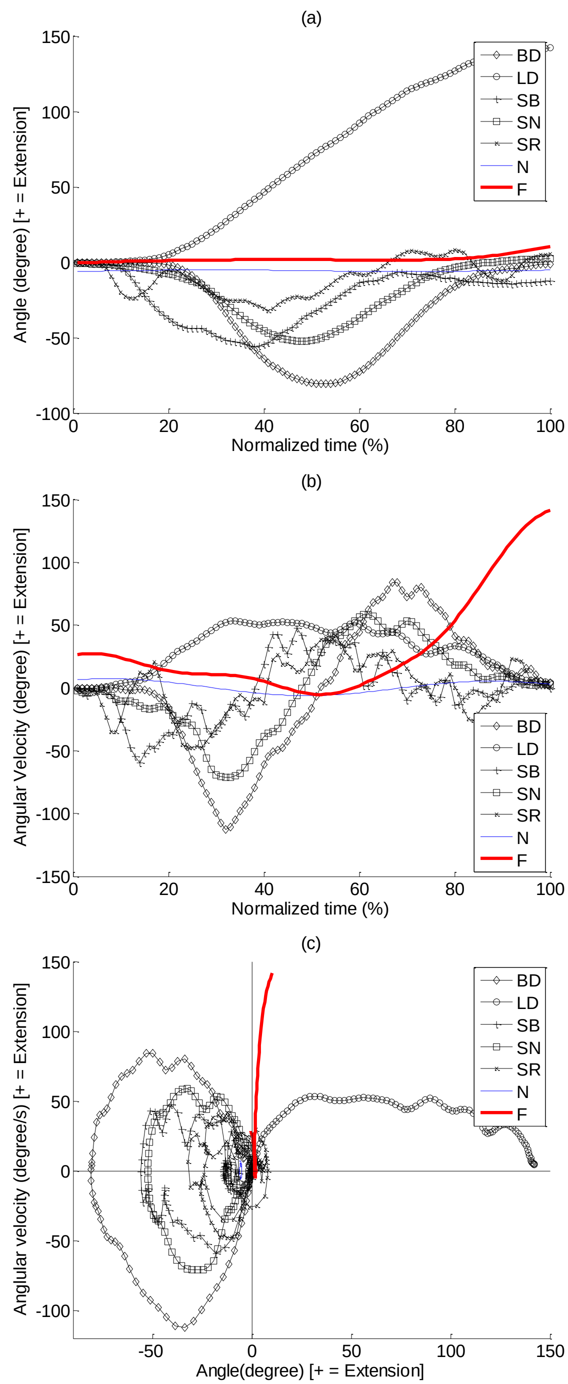

Figure 16 – Trunk angular kinematics during ADLs and falls; (a) and (b) ensemble average profiles; (c) ensemble average angular phase plots; (BD: bending over and rising up; LD: lying down; SB: sitting into a bucket seat; SN: sitting down; SR: sitting into a rocking chair; N: normal walking; F: slip-induced backward falls)

Table 11 – Summary of peak trunk angular kinematics during ADLs and slip-induced backward falls

Type	Angular velocity (°/s) (mean/SD)		Angle (°) (mean/SD)	
	Flexion	Extension	Flexion	Extension
N*	7 (5.7)	9.5 (3.4)	6.8 (3.1)	-
F	18 (35.5)	139.7 (34.7)	2.4 (5.5)	11 (5.6)
BD	131.6 (23.2)	118.7 (28)	82.4 (7.7)	0.8 (0.8)
LD	7.4 (7.7)	90 (19.7)	0.5 (0.4)	142.7 (8.3)
SN	85.4 (17.4)	84.7 (14.7)	53.6 (14.6)	4.4 (6.2)
SR	96.7 (21.3)	89.8 (20.6)	56.5 (13.5)	14.3 (8.8)
SB	100.5 (43.3)	112.1 (42.5)	73.1 (22.6)	3.6 (4.3)

* N: normal walking; F: backward fall; BD: bending over; LD: lying down; SN: sitting on a normal chair; SR: sitting into a rocking chair; SB: sitting into a bucket seat

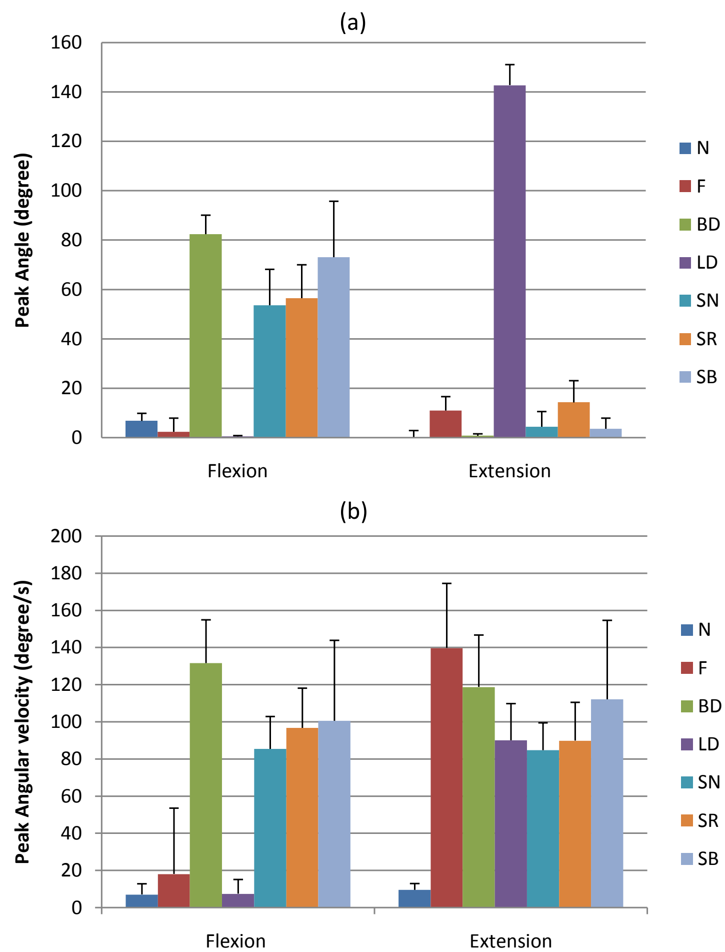

Figure 17 – Comparison of peak trunk angular kinematics (a – angle; b - angular velocity) during ADLs and slip-induced backward falls (error bar indicates 1SD)

4.6.9. Discriminant analysis

The trunk sagittal angular kinematics from all the ADL trials and backward fall trials were plotted in Figure 18. The data points in this phase plots were the basis for the discriminant analysis in the current study. The objective of the discriminant analysis was to create the discriminant functions that offer the best separation in between the data points from backward falls and those from ADLs.

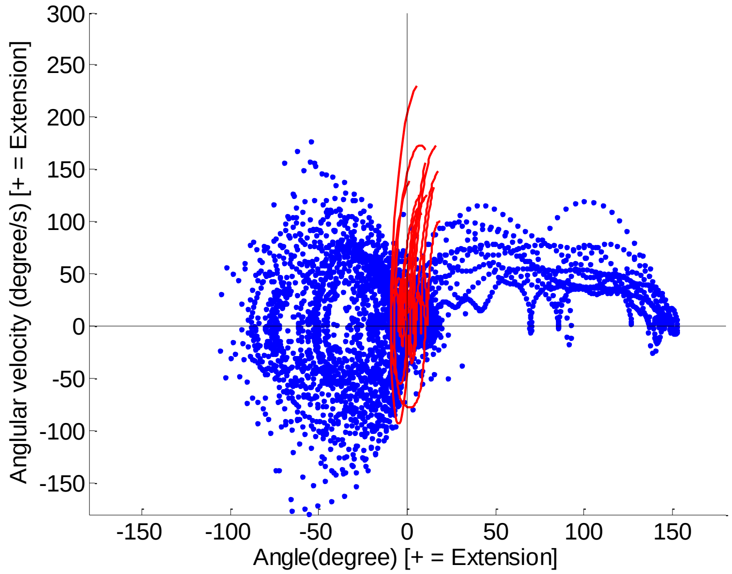

Figure 18 – Composite illustration of trunk angular phase plots from all the ADL trials (indicated by dots) and all the backward fall trials (indicated by lines)

Because algorithm I utilized two-dimensional information (α and ω), both linear and quadratic discriminant forms were implemented. For algorithm II, only the linear discriminant form was implemented. The resultant discriminant functions are listed below:

$$F_{Algorit\ hmI-L} = 0.83 + \begin{pmatrix} \alpha \\ \omega \end{pmatrix} \cdot \begin{pmatrix} 0.00 \\ -0.03 \end{pmatrix}$$

Eq. 5

$$F_{Algorit\ hmI-Q} = -1.26 + \begin{pmatrix} \alpha \\ \omega \end{pmatrix} \cdot \begin{pmatrix} -0.01 \\ -0.01 \end{pmatrix} + \begin{pmatrix} \alpha \\ \omega \end{pmatrix} \cdot \begin{pmatrix} 0.01 & -0.00 \\ -0.00 & 0.00 \end{pmatrix} \cdot \begin{pmatrix} \alpha \\ \omega \end{pmatrix}^{-1}$$

Eq. 6

$$F_{Algorit\ hmII} = 0.82 + \omega \cdot (-0.03)$$

Eq. 7

The discrimination performances of the above three functions were shown in the instantaneous ROC (ROC[i]) plots (Figure 19). As illustrated, algorithm I-Q (Eq. 5) achieved a good discriminant performance, with an Area Under Curve (AUC) of 0.8908 (Table 12). The performances of algorithm I-L (Eq. 6) and algorithm II (Eq. 7) were moderate, with an AUC of 0.7392 and 0.7247, respectively. Therefore, algorithm I-Q was considerably better than both algorithm I-L and algorithm II in terms of detecting each instantaneous moment (data point in angular phase plot, Figure 18) into either fall or non-fall cases.

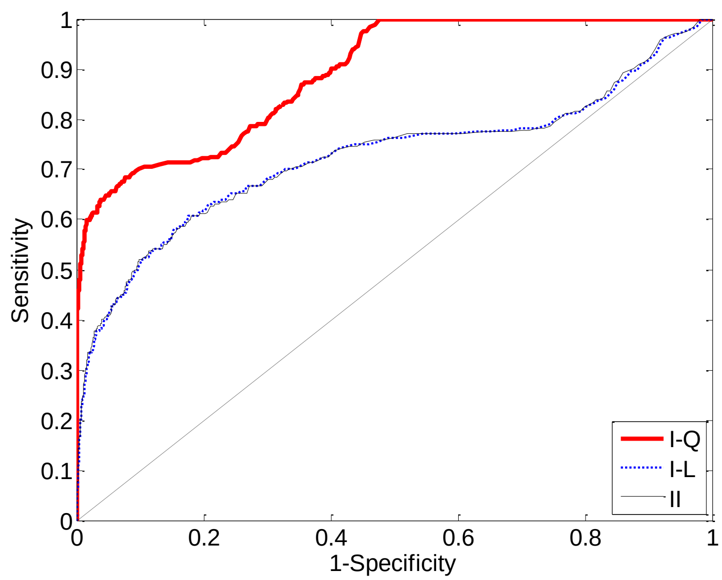

Figure 19 – Instantaneous ROC (ROC[i]) curves of three fall detection algorithm configurations (I-Q: new algorithm in quadratic form; I-L: new algorithm in linear form; II: baseline algorithm)

Based on the predictive values derived from the above three discriminant functions (algorithm I-Q, I-L and II) for each data point, the activity ROC (ROC[a]) analyses were conducted to quantify the performance of each algorithm in detecting each activity (data trial composed of a group of data points) into fall or non-fall cases. As shown in Figure 20, the algorithm I-Q achieved an excellent discriminant performance, with an AUC of 0.9957, approaching an ideal performance level (AUC =

1). Both the algorithm I-L and algorithm II performed equally well, with AUC being 0.8632 and 0.8803, respectively.

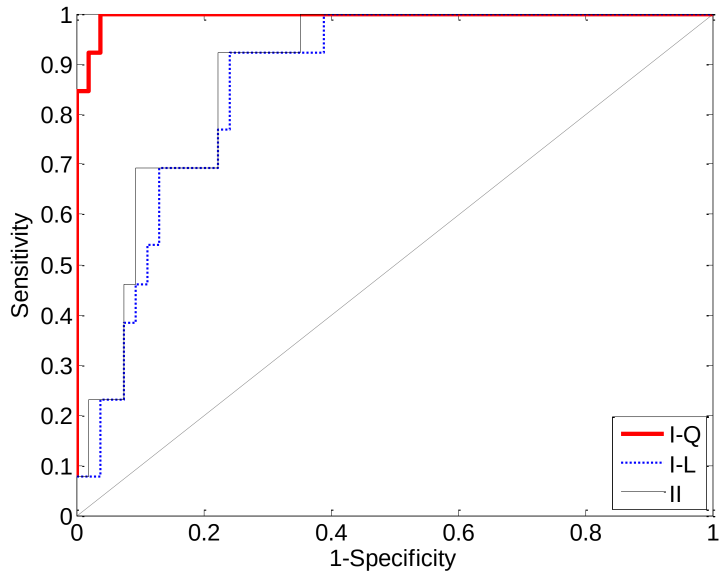

Figure 20 – Activity ROC (ROC[a]) curves of three fall detection algorithms (I-Q: new algorithm in quadratic form; I-L: new algorithm in linear form; II: baseline algorithm)

The influence of *TH* on sensitivity (Sn) and specificity (Sp) at the activity level was illustrated in Figure 21. In general, the increasing *THs* were found to be associated with an increasing sensitivity but a decreasing specificity. For the algorithm I-Q (Figure 21-a), there existed a range of thresholds (-4.336 ~ -3.633) in which both sensitivity and specificity can achieve a satisfactory level (Sn = 92.31%, Sp = 98.15%) (Table 12). That is, an algorithm configured with any of these thresholds would have similar high detection performance. An algorithm configured with a threshold outside the above mentioned range would produce an undesirable performance in practice. For both algorithm I-L and algorithm II, however, it was not feasible to achieve a high level of sensitivity and specificity at the same time (Figure 21-b, c). With higher priority given to specificity, a range of *TH*s (-2.433 ~ -2.273) were considered optimal for algorithm I-L, with sensitivity being 69.23% and specificity being 87.04% (Table 12). Similarly, a range of *TH*s (-2.548 ~ -2.64) were considered optimal for algorithm II, with sensitivity being 69.23% and specificity being 90.74% (Table 12).

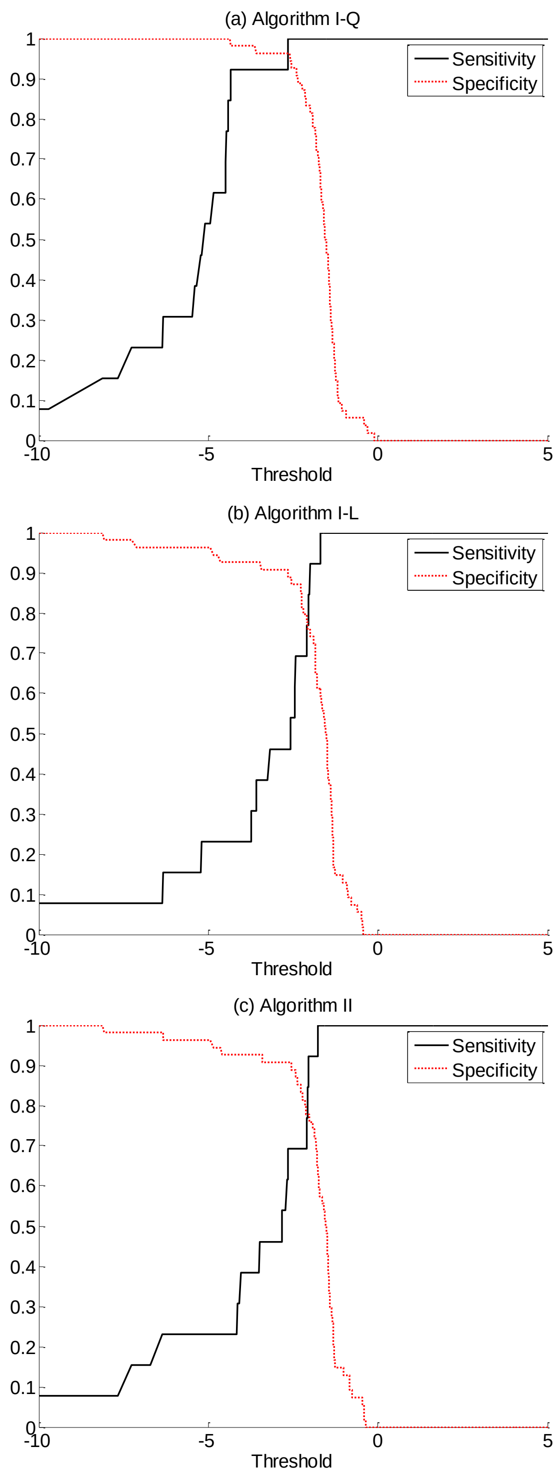

Figure 21 – Relationship between fall detection thresholds (*TH*) and sensitivity/specificity of different algorithms

As summarized in Table 12, algorithm I-Q was able to achieve an excellent fall detection performance (as quantified by sensitivity and specificity), much better than the other two algorithms (I-L and II). Though their specificities were good, both algorithm I-L and algorithm II only achieved a moderate level of sensitivity.

Table 12 – Summary of discriminant analysis

	AUC of ROC[i]	AUC of ROC[a]	Range of TH	Sensitivity	Specificity
Algorithm I-Q	0.8908	0.9957	-4.336 ~ -3.633	92.31%	98.15%
Algorithm I-L	0.7392	0.8632	-2.433 ~ -2.273	69.23%	87.04%
Algorithm II	0.7247	0.8803	-2.548 ~ -2.64	69.23%	90.74%

* TH: Detection threshold; "fall" was detected whenever the predictive value from the discriminant function was less than threshold; Note that the generic threshold for each algorithm was taken as the midpoint of the corresponding range of TH.

4.7. Discussions and Conclusions

The purpose of the current study was to explore the possibility of distinguishing slip-induced backward falls from ADLs. It was expected that the trunk angular kinematics might have unique motion features that could be used to distinguish falls from ADLs.

4.7.1. Biomechanical characteristics of ADLs and backward falls

Various fall event detection algorithms have been proposed over the years (see Table 12 in Chapter 5). Until now, however, little research has been conducted on the characteristics of fall activities that differ from ADLs from a biomechanics perspective. Wu (2000) studied the linear velocity characteristics of the trunk during three different types of falls and several different ADLs. It was suggested that both horizontal and vertical trunk velocity could be used for automatic detection of fall events. Such findings, however, have not been utilized to develop an ambulatory fall detection algorithm, possibly due to the current technical limitations of inertial sensors (see Chapter 2) in measuring the linear velocity directly. In the author's opinion, it is beneficial to build the knowledge regarding the unique motion features of falls before designing a new fall detection algorithm. Meanwhile, the potential motion features should be easily measurable by the current ambulatory sensors. With these considerations, the current study investigated the possibility to differentiate falls from ADLs utilizing trunk angle and angular velocities, which can be directly measured by an inertial measurement unit (IMU).

As expected, the slip-induced backward falls exhibited a unique feature in trunk angular kinematics compared to ADLs. As illustrated in Figure 16-c, the kinematic measurements of backward falls were clearly distinguishable from those of ADLs in an angular phase plot. The majority of kinematic measurements of ADLs were dispersed within the 2nd and 3rd quadrants, and a flattened region close to the positive x axis within the 1st quadrant of the angular phase plot. On the contrary, the kinematic measurements of the backward falls were mainly located in a flattened region close to the positive y axis within the 1st quadrant of the angular phase plot. That is, the trunk kinematics of the backward falls were unique in terms of the simultaneous occurrence of an extremely high extension angular velocity and extension angle. Such distinguishable distributions of falls and ADLs in an angular phase plot formed the foundation for the discriminant analysis in the current study.

The trunk angular kinematics obtained from the current study was generally comparable to the findings in the literature. During normal walking, the trunk segment was dominated by a slight flexion, with minimum and maximum flexions occurring at the toe off and heel contact, respectively. The profiles of trunk angle and angular velocity were consistent with those in the literature (McGibbon & Krebs, 2001; Syczewska, Oberg, & Karlsson, 1999). Quantitatively, the average trunk angular velocity and flexion angle were found to be 7~9.5°/s and 6.8° in the current study. As a comparison, Syczewska et al. (1999) found a forward leaning of the whole spine of 4~5°. Mc Gibbon et al. (2001) found that for healthy young adults, the range of trunk angular velocity was within 34°/s. During ADLs, in the current study, the average peak angular velocity was 118.7 °/s for bending over and 84.7~112.1 °/s for three types of sitting down. Similarly, Nyan et al. (2006) found the peak angular velocities being ~125 °/s for bending over, and ~100 °/s for sitting down.

During backward falls, however, the results from the current study were substantially different from those in literature. Nyan et al. (2006) observed an average peak extension angular velocity to be ~450 °/s, much higher than that (139.7 °/s) measured in the current study. Because the measurements of the same motion agreed well between motion analysis system and inertial sensors in the current study, the above discrepancies were likely to be due to the differences in study designs. More specifically, the backward falls in the current study were stopped by the overhead harness in the middle of the fall dynamics while in the previous study the participants were allowed to impact the ground (covered by mattress). Therefore, it is likely that those high angular velocities observed in the previous study occurred in the latter phase of the fall dynamics, which was not measured by the current study.

The trunk segment was selected as the focus of the current study based on the practical consideration that trunk segment was an ideal site of sensor attachment for the purpose of Study 2. It is agreed by many researchers that the trunk segment is the optimal location for a fall detector due to its proximity to the body's center of mass and acceptable user compliance (Bourke, O'Brien, & Lyons, 2007b; Doughty, et al., 2000; Hwang, et al., 2004; Noury, et al., 2003). It should be acknowledged that other sensor locations (i.e., wrist and head) have also been investigated in previous studies (Degen, et al., 2003; Kangas, Konttila, Lindgren, Winblad, & Jamsa, in press; Lindemann, et al., 2005). Despite its superior usability, a wrist-based fall detector was deemed inapplicable due to its insufficient detection performance (Degen, et al., 2003; Kangas, et al., in press). Though the performance of head-based algorithm (Lindemann, et al., 2005) proved to be excellent, it is problematic for an head-attached ambulatory sensor to accomplish other tasks like ADL classification (Kangas, et al., in press), which was an important component for Study 2. Based on these considerations, the trunk segment was considered a suitable location with a good compromise between being practical and having a good performance. Therefore, the motion features of trunk segment were investigated in the current study to facilitate the development of the new fall detection algorithm.

4.7.2. Development of fall detection algorithm

In the current study, discriminant analysis was performed to construct the discriminant function that could offer the optimal separation between motion characteristics of ADLs and those of slip-induced backward falls. A fall detection algorithm constructed by such an approach was expected to utilize the two-dimensional information (α and ω) in an integrative manner, as discussed in Chapter 5. The two alternative forms (linear and quadratic) of discriminant functions were compared in order to determine the optimal form for constructing the actual fall detection algorithm for the Study 2.

Two types of ROC curves (ROC^{a} and ROC^{i}) were reported as overall performance measures of the fall detection algorithms involved in the current study. ROC curve as a standard index for diagnostic accuracy has enjoyed popularity in many different areas including clinical assessments (for review, see McFall & Treat, 1999; Zweig & Campbell, 1993). In fall event detection area, however, none of the previous studies (see Table 12 in Chapter 5) has ever utilized ROC to report algorithm performance. Instead, most of these studies (Table 12) adopted sensitivity and specificity as the performance indices for their detection algorithms. Despite providing valuable information as well as being the foundation for constructing an ROC curve, the sensitivity and specificity measures are limited to a specific algorithm configuration as shown in Study 2. In other words, these two measures are dependent on the choice of detection threshold for a given algorithm, as illustrated in Figure 21 and discussed below. Therefore, it is recommended that for future fall detection studies, ROC curves are reported in addition to other performance measures (i.e., sensitivity and specificity) to facilitate the comparison of different algorithms.

The reluctance to report ROC curves in previous studies may come from the fact that traditional ROC curves are not readily suitable as a faithful measure of a fall detection algorithm. In order to faithfully reflect the detection performance of the discriminant functions, a new type of ROC curve (ROC^a) was designed and implemented in the current study. The ROC^a curve quantifies the detection performance at an individual activity level. As a contrast, the ROC^i curve, which is essentially the same as conventional ROC curve, quantifies the detection performance at the level of individual measurement. The results (Table 12) from the current study indicated that there were dramatic differences between the AUC measures of ROC^a and ROC^i. Such differences can be attributed to the difference in the way ROC^a and ROC^i assign the detection outcomes. For example, for an actual fall trial, ROC^a would consider the entire activity to be one true positive as long as one data point from that fall trial can be detected as fall. For the same fall trial, however, ROC^i would consider only one data point as a true positive if only one data point can be detected as fall and the rest of the trial as false negatives. Therefore, the ROC^a curve can more faithfully reflect the overall performance of a fall detection algorithm.

The quadratic type of discriminant function was deemed suitable for constructing the new fall detection algorithm. As shown in Table 12, the algorithm I-Q had a close to ideal detection performance (AUC of ROC^a = 0.9957), which was considerably higher than that of the algorithm I-L (AUC of ROC^a = 0.8632). The performance of the algorithm I-L was comparable to that of the algorithm II (AUC of ROC^a = 0.8803), which was the baseline algorithm using only one-dimensional information. In other words, with the linear form of the discriminant function, the added body orientation information does not offer advantages to the algorithm using only motion intensity information.

Sensitivity and specificity associated with a particular algorithm configuration have important implications to fall event detection in practice. On one hand, without a sufficiently high level of sensitivity, a large number of actual falls will be falsely detected as ADLs. On the other hand, without a sufficiently high level of specificity, a large number of ADLs will be falsely detected as falls, which would negatively impact the user compliance of a fall detection system. A high rate of misdetection would lead to loss of confidence in the fall detector by the end user. In practice, however, for a span of time, the number of falls that one would encounter is limited relative to the number of ADLs occurring during one's daily life. Therefore, a slight decrease in sensitivity may not cause noticeable difference while a slight decrease in specificity would obviously result in substantial increases in false alarms. As suggested by a previous study (Kangas, et al., in press), some compromises between specificity and sensitivity might be necessary depending on the user acceptance of false alarms. In configuring a specific algorithm, it is the author's opinion that higher priority should be given to maintain a satisfactory level of specificity. This concept formed the foundation for configuring the actual fall detection algorithm and to perform individual calibration in Study 2. Nevertheless, it is desirable that both sensitivity and specificity reach a satisfactory level simultaneously.

Unfortunately, it was rarely feasible to achieve a satisfactory level in both sensitivity and specificity simultaneously. As illustrated in Figure 21, increases in detection threshold were usually associated with increases in sensitivity but decreases in specificity, or vice versa. Similar phenomenon was also observed in previous studies (Diaz, et al., 2004; Noury, et al., 2003). Noury et al. (2003) found that higher sensitivity was always associated with higher rates of false alarm. Diaz et al. (2004) also witnessed that as the accuracy of the true falling events detection increased, the rate of false alarm increased as well. Therefore, choice of a detection threshold is really a determining factor for the performance measures of a given detection algorithm. One idea of making a good choice of threshold is to apply optimization technique. Either the costs or the rate of misdetections and false alarms could be minimized, given that the costs of inaccurate detections or the a priori probability of fall accidents can be quantified.

It may be argued that other classification techniques, instead of the threshold technique, should be adopted in developing a fall detection algorithm. These techniques include neural networks (Kiani, et al., 1998), wavelet technique (Najafi, et al., 2003; Nyan, Tay, Seah, et al., 2006), pattern matching (Mathie, Celler, et al., 2004), and so on. However, as explained by Karantonis et al. (2006), the real-time nature of fall detection task imposed several constraints on choosing a classification technique. First of all, there is no a priori knowledge regarding the future events. Second, despite the availability of the past events, the ability for the detection system to retrieve and process such information may be limited by the hardware online processing capability and onboard buffering capability. Third and most critical to prior-to-impact type of algorithm design, rapid response to the fall event limits the computing time available for a classification technique to use, and thereby limits the complexity of the algorithm. Therefore, as is true with the previous fall detection studies, the nature of fall event detection dictates the choice of threshold technique in the algorithm design.

4.7.3. Conclusions

In conclusion, the slip-induced backward falls was characterized by a simultaneous occurrence of an extremely high trunk extension angular velocity and a slight trunk extension angle. Such motion features of falls were found to be clearly distinguishable from those of ADLs. The discriminant analysis indicated that the quadratic form of the discriminant function, with higher fall detection performance in terms of ROC[a], was suitable for developing the new fall detection algorithm. In addition, the relationship between fall detection threshold and two of the performance measures (sensitivity and specificity) suggested individual calibration may further enhance the effectiveness of the new detection algorithm.

Chapter 5

5. STUDY 2: FALL EVENT DETECTION

5.1. Objective and Hypotheses

Study 2 was a laboratory study using inertial sensors to measure the kinematic motion characteristics of slip-induced falls and various types of ADLs. This study was designed to apply the algorithm construction concept obtained from Study 1 into the inertial measurement datasets and to evaluate the performance of the new fall event detection algorithm. Additionally, this study aimed to evaluate the utility of the individual calibration function provided by the IAM framework.

It was hypothesized that:

- The new algorithm would have significantly higher sensitivity and specificity, and lower response time than the baseline algorithm.

- The new algorithm with individualized fall detection threshold obtained from the individual calibration would have significantly higher sensitivity and specificity, and lower response time than the one with generic threshold.

5.2. Participants

The same 10 elderly participants (> 65 years old) from Study 1 were involved in this study. Informed Consent (IRB #07-628) was approved by the IRB committee at Virginia Tech and obtained from the participants prior to any data collection. The summary of their information can be found in Table 3.

5.3. Apparatus

One IMU (Inertia-Link, MicroStrain, Inc., USA) was placed close to the sternum. The Inertia-Link is a miniature orientation sensor, which is capable of measuring 3D orientation, 3D acceleration, and 3D angular velocity. With respect to the orientation performance, the Inertia-Link has an angular resolution of $<0.1^\circ$, static accuracy of $\pm 0.5^\circ$ and dynamic accuracy of $\pm 2.0^\circ$ RMS (MicroStrain Inc., 2007). The dynamic ranges for the acceleration and angular velocity outputs are $\pm 300^\circ/s$ and 5g, respectively (MicroStrain Inc., 2007). The sampling rate was set to be 100Hz.

Another IMU (WiTilt v2, SparkFun Electronics, USA) was placed on the right thigh (front side and mid-point) of the participant. WiTilt contains a miniature tri-axial accelerometer (MMA7260Q, Freescale Semiconductor, USA), with selectable dynamic ranges of 1.5g, 2g, 4g and 6g. The typical sensitivity is 800mv/g at 1.5g (Freescale Semiconductor, 2005). During this study, the dynamic range of the IMU was set to be 6g. The sampling rate was set to be 100Hz.

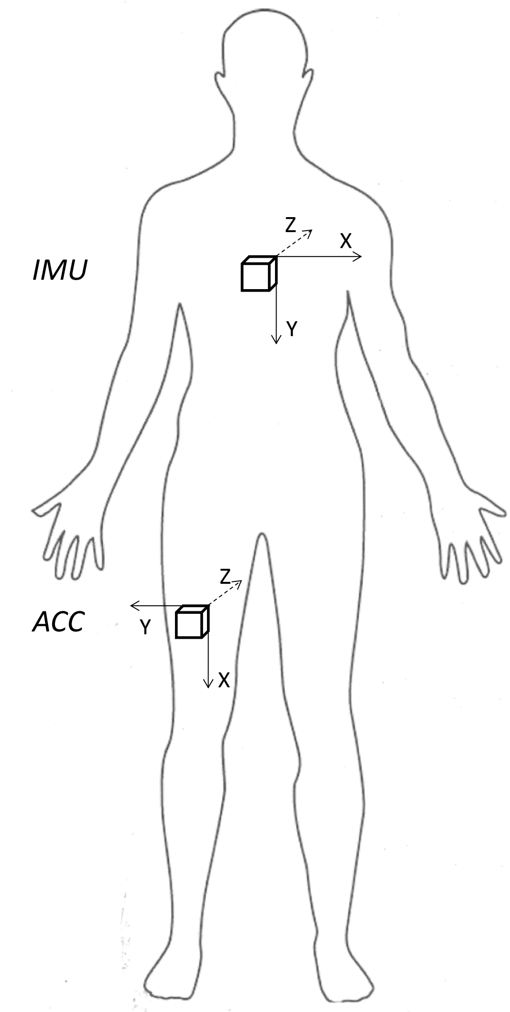

Figure 22 – Sensor placement and orientation. IMU: Inertial Measurement Unit; ACC: Accelerometer

The adapted biomechanical model (Lockhart, et al., 2003) with an additional marker on the sternum was used in this study. A six-camera infrared motion capture system (ProReflex MCU 240, Qualisys, Gothenburg, Sweden) was used to measure the 3D position of the reflective markers. The sampling frequency was 100Hz. The vertical position of the marker on the sternum was used to identify the motion phases of the falling. The whole body motion analysis data was used as the baseline reference for the purpose of evaluating the ADL classification performance.

The same walking track with movable floor surfaces as described in Study 1 was used in this study. An overhead harness system was used to prevent the participants' other body parts except feet from hitting the ground. The length of the harness was set in such a way to allow vertical falling of the trunk up to 20cm from the standing posture.

Similar to Study 1, regular living furniture (bed, desk, chair, etc) was used.

5.4. Procedures

5.4.1. For ADLs

Participants were first required to change into experimental clothing (short and sleeveless shirt). This was to facilitate the attachment of the IMU sensors and to minimize the possible interference of the clothing on the data measurement.

An ADL protocol composing of 5 activities (Figure 7) was performed by all the participants. Each participant performed these ADLs in an order as specified by Table 5. For each posture, the participants were required to maintain the particular posture for 5 seconds. All the timing information was provided to the participants via auditory cues by the experimenter. The participants were required to perform them 'as naturally as possible' at their self-selected pace.

Prior to data collection, each participant were allowed 10-15 minutes practice time to get familiar with the ADL protocol.

5.4.2. For normal walking and falls

This study implemented the same procedure, as described in Study 1, to measure the data during normal walking and slip-induced falls.

Due to the similarity in the procedures, the experiment testing of Study 1 and Study 2 were actually conducted together.

5.5. Data Reduction

5.5.1. ADL classification

The motion analysis data was used as a reference measurement. Segmentation of the captured motion file into static phases and dynamic phases and documentation of the nature of the posture/activity was performed subjectively by an experimenter. The time resolution of this activity log was expected to be about 0.1s.

Automatic classification of daily activities was based on the algorithm described in Chapter 3. The computer-generated activity log was then compared with the activity log generated manually from the motion analysis system for each participant.

5.5.2. Fall event detection

All of the participants were randomly assigned into two groups. The data from the first group (4 participants) were used as the training dataset to construct the new detection algorithm. The data from the second group (6 participants) were used as the validation dataset to validate the performance of the new detection algorithm.

The quadratic form of discriminant analysis as specified in Study 1 was performed on the training dataset in order to derive the discriminant function, $F_{AlgorithmI}(a, \omega)$, for the new algorithm (algorithm I). The generic detection threshold for algorithm I was determined based on the relationship between *TH* and sensitivity/specificity, and the following rules:

- If a specific *TH* (or a range of *TH*s) could achieve the highest sensitivity and the highest specificity simultaneously, this *TH* (or the mid-point of that range of *TH*s) was selected as the optimal *TH* for that algorithm.

- If no *TH* can achieve the highest sensitivity and the highest specificity simultaneously, the optimal *TH* for that algorithm had to satisfy: a) specificity over 95%; and b) the highest sensitivity. In case that no *TH* could achieve specificity over 95%, the optimal *TH* for that algorithm was set to be a *TH* associated with the highest specificity with non-zero sensitivity. This rule gave priority to reduce the rate of false alarm over to increase the accuracy of fall detection.

The algorithm configuration with the generic threshold was termed as algorithm I-A. For algorithm I-A, a specific activity trial would be detected as fall if, for any data pair (α, ω) from this trial,

$$F_{Algorit\ hmI}(\alpha, \omega) < TH,$$

Eq. 8

otherwise, this trial would be detected as non-fall.

The baseline algorithm (algorithm II) was formulated based on the literature (Nyan, Tay, Tan, et al., 2006). The associated discriminant function, $F_{AlgorithmII}(\omega)$, was in the form of

$$F_{Algorit\ hmII}(\omega) = -\omega,$$

Eq. 9

To be faithful to the literature, the generic threshold for algorithm II was set as -130°/s. The algorithm configuration with this computed threshold was termed as algorithm II-A.

For algorithm II-A, a specific activity trial would be detected as fall if, for any data point (ω) from this trial,

$$F_{Algorit\ hmII}(\omega) < TH,$$

Eq. 10

otherwise, this trial would be detected as non-fall.

To facilitate the description of the fall dynamics, the following events and duration measure were defined (Figure 23):

- Fall initiation: an event same as slip start (Lockhart, et al., 2003) when the forward heel velocity occurs after heel contact.
- Fall detection: an earliest event when the fall detection algorithm detects a fall

- Fall completion: an event when the reflective marker on the trunk drops to a vertical minimum[3].

- Response time: the time between fall initiation and fall detection. This variable was defined to describe how much time would be required for a fall to be detected after it was initiated.

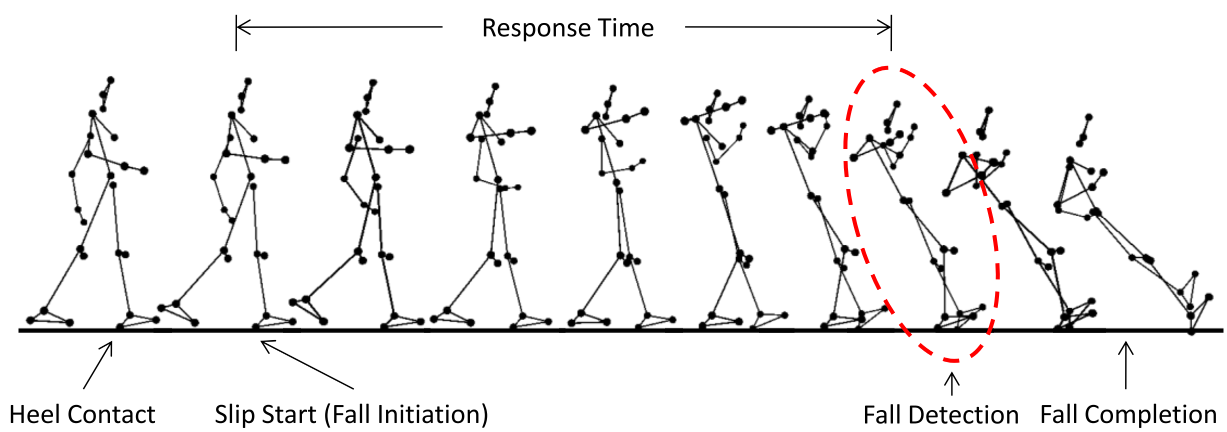

Figure 23 – Timing variables associated with slip-induced backward fall

ROC[a] was used to illustrate the overall performance of the algorithm I and II. The designation of detection outcome followed the rule specified in study 1 and was also illustrated in Table 13.

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Table 13 - Definition of fall detection outcome

		Activity detected	
		As fall	As ADL
Actual activity	Fall	true positive (TP)	false negative (FP)
	ADL	false positive (FP)	true negative (TN)

The following detection performance measures were derived from ROC[a].

3 Due to the protection from the harness, no actual impact could result from falling. This event will thus be earlier than the actual time of impact as observed in a real-life fall accident scenario.

$$Sensitivity = \frac{TP}{TP+FN} \times 100\%$$

Eq. 11

Sensitivity was used to quantify the rate of correctly detected falls relative to the total amount of actual falls. The opposite aspect of sensitivity is the rate of misdetection (misdetection + sensitivity = 100%). The higher the sensitivity is, or the lower the rate of misdetection is, the better the detection performance will be.

$$Specificity = \frac{TN}{TN+FP} \times 100\%$$

Eq. 12

Specificity was used to quantify the rate of correctly detected ADLs relative to the total amount of ADLs. The opposite aspect of specificity is the rate of false alarm (false alarm + specificity = 100%). The higher the specificity is, or the lower the rate of false alarm is, the better the detection performance will be.

5.5.3. Individual calibration

The concept of individual calibration can be found in Chapter 3. In the current study, the individual calibration algorithm was performed for each individual. Specifically, the predictive values were first obtained by applying the obtained discriminant function to all the ADL trials for a given individual. The search for an individualized *TH* started from the minimum predictive value and stopped until the specificity for that individual dropped below 95%. In other words, the minimum predictive value associated with 95% specificity was regarded as the temporary *TH* for that individual. The higher value between temporary *TH* and the generic *TH* was then taken as the individualized *TH*. The algorithm I configured with the individualized *TH* was termed as algorithm I-B.

All of the data processing was performed in a local computer using a custom-designed MATLAB program (MATLAB 2007a, MathWorks, USA).

5.6. Statistical Analysis

A one-way within-subject ANOVA was conducted with the algorithm configuration as the within-subject independent variable and the response time as the dependent variable. The algorithm configuration had 3 levels: algorithm I-A (new algorithm with generic threshold), algorithm I-B (new algorithm with individualized threshold), and algorithm II-A (baseline algorithm). The statistical model is shown below:

$$y_{ijk} = \mu + \alpha_i + \gamma_j + \alpha\gamma_{ij} + \varepsilon_{k(ij)}$$

$$E(MS_A) = n\sigma_\alpha^2 + \sigma_{\alpha\gamma}^2 + \sigma_\varepsilon^2$$

$$E(MS_S) = a\sigma_\gamma^2 + \sigma_\varepsilon^2$$

$$E(MS_{A\times S}) = \sigma_{\alpha\gamma}^2 + \sigma_\varepsilon^2$$

Source	df	SS	MS	F
Between				
S	*n-1*	SS_S		
Within				
A	*a-1*	SS_A	MS_A	$MS_A/MS_{A\times S}$
A × S	*(a-1)(n-1)*	$SS_{A\times S}$	$MS_{A\times S}$	
Total	*an-1*	SS_{total}		

where α_i, γ_j, and $\alpha\gamma_{ij}$ denote the main effect of the within-subject factor *A* (the algorithm configuration), the random effect due to participant *S*, and their interaction, respectively. Symbols *n* and *a* represent the number of participants and the level of the within-subject factor *A*.

Explicit test for normality (Shapiro-Wilk W Test) was performed. In the event when considerable deviation from normality of the dependent variables was found and simple transformation still cannot achieve normality, appropriate non-parametric test would be used. Mauchly's sphericity test was performed and if needed (in case of significant violation of sphericity assumption), Greenhouse-Geisser correction was performed to adjust the significant value (*p*-value) accordingly.

A significance level of $p \leq 0.05$ was used for hypothesis testing. ANOVA test was performed in SAS 9.1 (SAS Institute, USA). All the descriptive statistical analyses were performed in JMP 7.0 (SAS Institute, USA).

5.7. Results

5.7.1. Classification of Activity of Daily Living

Totally 179 ADL trials (including normal walking trials) were collected and subject to the ADL classification algorithm. As shown in Table 14, three types of ADLs (bending over, lying down and normal walking) were classified without any misdetection. One sitting down trial was misdetected as bending over. Four other trials (one SR and three SR) could not be recognized by the algorithm. Of all five misdetection trials, three resulted from IMU measurement errors and two were due to the difficulty to detect a clear static posture at the end of the trial by the algorithm. Overall, the ADLs in the current study were able to be classified with only 2.8% misdetection rate.

Table 14 – Summary of ADL classification

	Actual type	# of trials	Classified as
Correct classification	BD	29	BD
	LD	30	LD
	SB	30	
	SN	28	Sit down
	SR	27	
	N	30	N
Misdetection	SN	1	BD
	SN	1	unknown
	SR	3	unknown

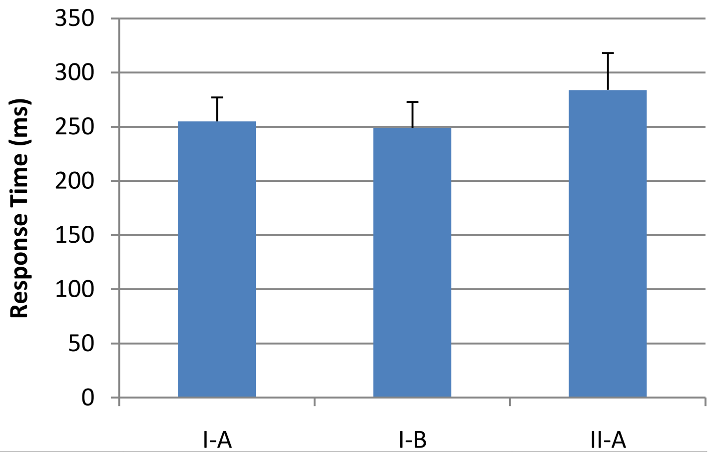
BD: bending over; LD: lying down; SB: sitting into a bucket seat; SN: sitting on a normal chair; SR: sitting into a rocking chair; N: normal walking

5.7.2. Response time

The response time (RT) was obtained by processing all the fall trials with three algorithm configurations: I-A (with generic threshold), I-B (with individualized threshold), and II-A (baseline). As indicated by the Shapiro-Wilk W tests, no significant departure from normality was found (I-A: W = 0.9475, p = 0.6857; I-B: W = 0.8784, p = 0.1818; II-A: W = 0.8817, p = 0.1954). No significant violation of sphericity assumption was found, neither (Mauchly criterion = 0.4821, p = 0.1121).

The ANOVA test indicated that the algorithm configuration had a significant effect on the RT (p = 0.0002). Post-hoc paired-t tests indicated that algorithm I-B had a significantly (p = 0.0492) lower RT than algorithm I-A (Figure 24), though the difference in RT was only 2.4% or 6ms (in average).

Furthermore, both algorithm I-A (p = 0.0008) and I-B (p < 0.0001) had a significantly lower RT than algorithm II-A. For example, the RT of algorithm I-B was, in average, 35ms (or 14.1%) lower than that of algorithm II-A. Overall, the algorithm I-B was associated with the lowest response time. Therefore, the individualized *TH* showed advantage in terms of reducing the time for the algorithm to detect a fall event.



	I-A	I-B	II-A
Mean	255	249	284
SD	22	24	34

Figure 24 – Response time (ms) of 3 different algorithm configurations (I-A: new algorithm with generic threshold; I-B: new algorithm with individualized threshold; II-A: baseline algorithm)

5.7.3. Fall detection algorithms

For the purpose of modeling, four participants' data (69 ADL trials and 6 slip-induced backward fall trials) were used as the training dataset and analyzed for deriving the fall discriminant functions. The discriminant function for algorithm I (quadratic form of the new algorithm utilizing α and ω) was found to be

$$F_{Algorit\,hmI} = -0.5251 + \begin{pmatrix}\alpha\\ \omega\end{pmatrix} \cdot \begin{pmatrix}-0.0586\\ -0.0070\end{pmatrix} + \begin{pmatrix}\alpha\\ \omega\end{pmatrix} \cdot \begin{pmatrix}0.0246 & -0.0010\\ -0.0010 & -0.0004\end{pmatrix} \cdot \begin{pmatrix}\alpha\\ \omega\end{pmatrix}^{-1}$$

Eq. 13

where a specific data trial was detected as fall if $F_{AlgorithmI}$ of any data pair (α and ω) of this trial was less than a predetermined detection threshold (*TH*). Otherwise, this data trial was detected as non-fall.

The discriminant function for algorithm II (baseline algorithm utilizing ω only) is shown below:

$$F_{Algorit\ hmII} = -\omega$$

Eq. 14

where a specific data trial was detected as fall if $F_{AlgorithmII}$ of any data point (ω) of this trial was less than a predetermined detection threshold (*TH*). Otherwise, this data trial was detected as non-fall.

The overall discrimination performances of the above two algorithms (I and II) at the activity level are illustrated in Figure 25. As shown, algorithm I achieved a very high discrimination performance, with an AUC of 0.9952, approaching an ideal performance level (AUC = 1.0). Though being slightly lower than that of algorithm I, the performance of algorithm II was also very high, with an AUC of 0.9855.

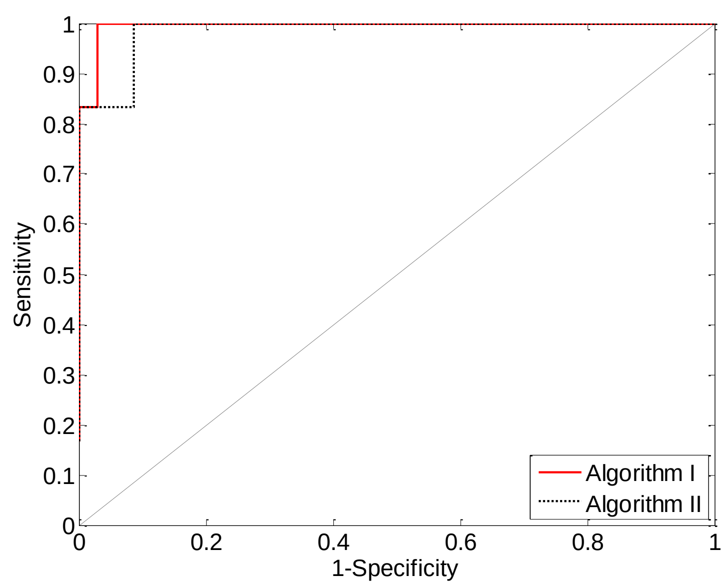


Figure 25 - ROC[a] curves of algorithm I and II during modeling

The generic (optimal) detection threshold (TH_{opt}) for algorithm I (Eq. 13) was determined based on the influence of *TH* on sensitivity and specificity at the activity level (Figure 26-a). As a compromise between sensitivity and specificity, the TH_{opt} was determined to be -4.994 for algorithm I. The sensitivity and specificity associated with this configuration (i.e., algorithm I-A) were found to be

100% and 95.65%, respectively. The TH_{opt} was set to be -130 for algorithm II, to be faithful to the baseline algorithm (ω < 130 °/s) from the literature (Nyan, Tay, Tan, et al., 2006). The sensitivity and specificity associated with this configuration (i.e., algorithm II-A) were found to be 83.33% and 92.75%, respectively.

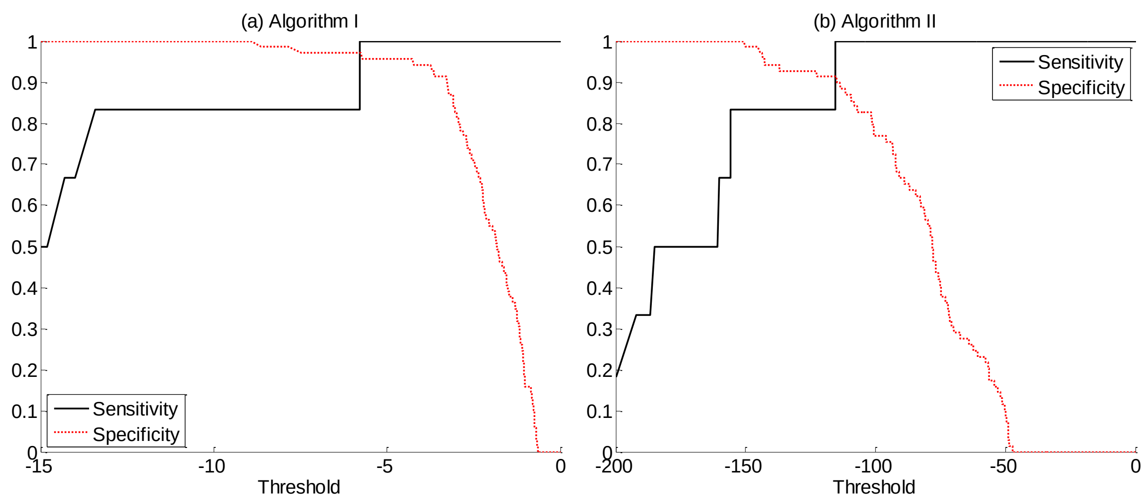


Figure 26 – Relationship between fall detection thresholds (*TH*) and sensitivity/specificity of algorithm I and II

5.7.4. *Validation of fall detection algorithms*

For the purpose of validation, the remaining 6 participants' data (105 ADL trials and 7 slip-induced backward fall trials) were used as the validation dataset and processed by algorithm I and II.

The overall discrimination performances of the algorithm I and II for the validation dataset are illustrated in Figure 27. The performance of the algorithm I using the validation dataset (AUC = 1.0) was slightly higher than that using the training dataset (AUC = 0.9952). For algorithm II, the performance with the validation dataset (0.9743) was slightly lower than that with the training dataset (0.9855).

As shown in Figure 28, for the specific algorithm configuration, the algorithm I-A achieved the same level of sensitivity (100%) but a slightly lower specificity (95.65% vs. 95%) with the validation dataset than with the training dataset. With the algorithm configuration II-A, the performance difference was noticeable. Compared with the training dataset, the validation dataset had a higher sensitivity (85.71% vs. 83.33%) but a lower specificity (90% vs. 92.75%).

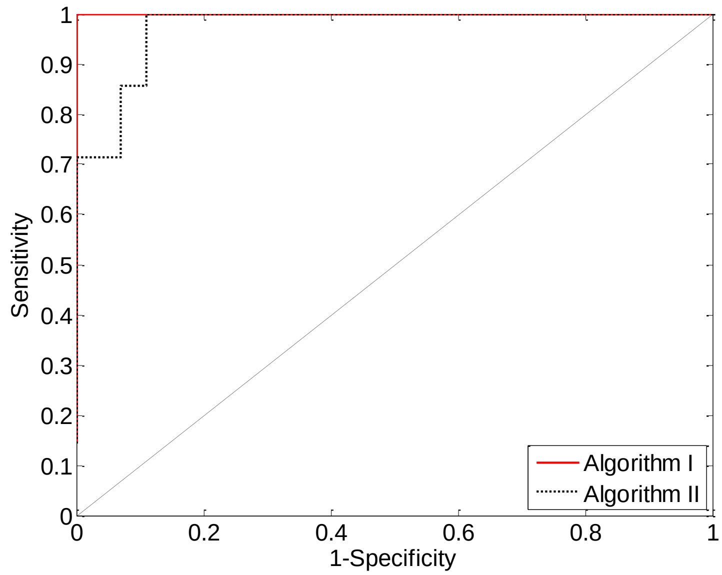
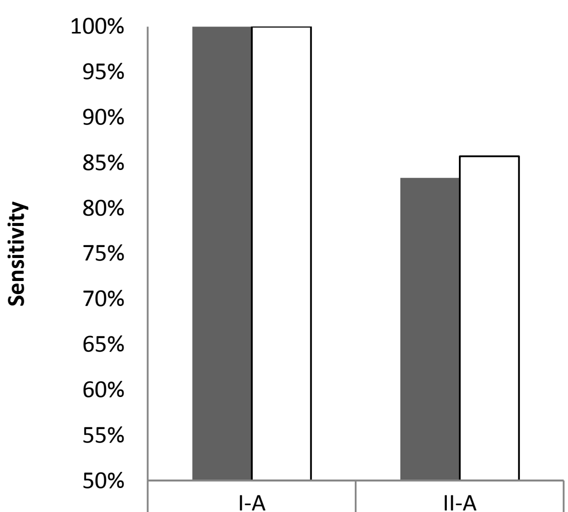
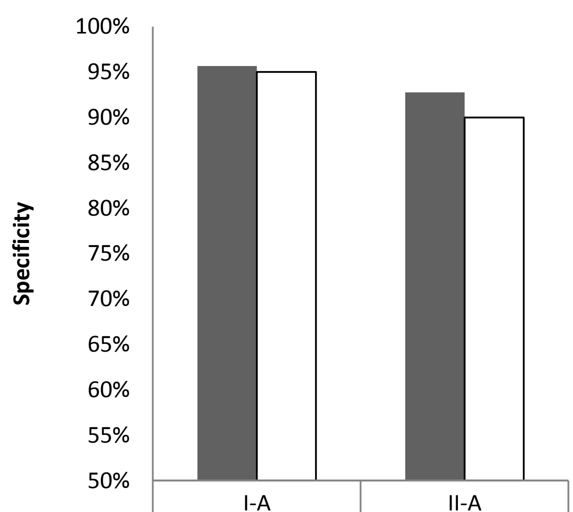


Figure 27 - ROC[a] curves of algorithm I and II during validation



	I-A	II-A
Training	100.00%	83.33%
Validation	100.00%	85.71%



	I-A	II-A
Training	95.65%	92.75%
Validation	95.00%	90.00%

Figure 28 – Sensitivity (left) and specificity (right) of algorithm configuration I-A and II-A with the training dataset and the validation dataset

Comparing the performance of different algorithms, algorithm I was found to outperform algorithm II by 14.29% in terms of sensitivity, and 5% in term of specificity. In other words, the new algorithm using two-dimensional information (α and ω) showed considerable advantage over the baseline algorithm using just one-dimension information (ω) in terms of higher sensitivity and specificity.

5.7.5. Individual calibration

The individual calibration was performed for all the participants using ADL data trials. The detection thresholds (*TH*) for four out of ten participants were able to be enhanced (Table 14). For each individual, another fall detection algorithm configuration (algorithm I-B) was constructed with algorithm I and individualized *TH* (Table 14). Consequently, for four out of ten participants, the algorithm I-B was different from the algorithm I-A. The overall sensitivity and specificity of algorithm I-B were found to be 100% and 95.27%. Compared to the algorithm configuration I-A (with the generic threshold), the algorithm I-B achieved the same level of sensitivity (100%) and an approximately same level of specificity (95.25% vs. 95.65%).

Table 15 – Fall detection thresholds (*TH*) before and after individual calibration

	Detection threshold (*TH*)	
Participant #	Before individual calibration	After individual calibration
O01	-4.994	-4.994
O02[a]	-4.994	**-2.8855**
O03	-4.994	**-3.8666**
O04	-4.994	-4.994
O05	-4.994	-4.994
O06	-4.994	-4.994
O07	-4.994	-4.994
O08	-4.994	**-3.5786**
O09	-4.994	-4.994
O10	-4.994	**-2.7634**

[a] Rows in bold indicates that *TH* were enhanced by individual calibration

5.8. Discussions and Conclusions

The findings from Study 1 provided the knowledge regarding the way to construct the fall discrimination functions and the function form that offers the best detection performance. Equipped with this information, the current study intended to apply the same discriminant analysis concept to inertial sensor measurements, to construct the new fall detection algorithms suitable for inertial measurements, and to evaluate its fall detection performances. The current study also aimed to explore the feasibility and the utility of the individual calibration algorithm. It was hypothesized that the new algorithm with individualized threshold would offer superior performance in terms of sensitivity, specificity, and response time.

5.8.1. ADL classification

In the current study, accurate and reliable ADL classification is a prerequisite for the individual calibration algorithm to function automatically. Within the IAM framework, the information about the type of the ADL activity is one of the inputs for the individual calibration algorithm. Even outside the context of the current study, ADL classification by itself offers a promising approach to objectively evaluate the effectiveness of experimental manipulations or medical interventions such as rehabilitation programs, surgeries, medications, and etc. (Bussmann, Tulen, et al., 1998).

The findings from the current study showed an excellent classification performance of the ADL classification algorithm. The misdetection rate was found to be 2.8%. A portion (two out of five) of these misdetections was due to the non-uniform movement patterns. As most real-world activities are non-uniform, it is advised to deploy more sophisticated ADL classification method in the future development for practical consideration. The performance from the current study compared favorably to those of the other algorithms in the literature. For example, the best-estimate threshold approach (Lyons, et al., 2005), which was the basis for the current ADL algorithm, achieved an overall accuracy ranging from 84% to 97% for different types of activities. By applying different techniques to detect different types of ADLs, Mathie et al. (2004) found an overall sensitivity of 97.7%. With a five-sensor configuration (IDEEA), Zhang et al. (2003) detected various ADLs with an overall identification rate of 98.7%. With an innovative wavelet technique, Najafi et al. (2003) was able to achieve an overall accuracy of 99% with just one sensor. Most recently, Karantonis et al. (2006) implemented a real-time ADL monitor system and observed an overall misdetection rate of 10.2%.

It should be acknowledged that many simplifications existed both in the algorithm itself and in the ADL testing protocol employed in the current study. In terms of the algorithm, one major simplification was to classify walking and bending over based on the length of the time interval between consecutive standing postures. In terms of the testing protocol, one major simplification was that the ADLs were not performed continuously. Instead, participants were asked to stand still at the beginning and the end of each trial. In addition, as is true for most of the similar studies, the types of ADLs in the current study were, by no means, are exhaustive or representative to all the ADLs that one would experience in daily life.

Nevertheless, such simplification of the ADL algorithm and the testing protocol was considered sufficient for the purpose of the current study, whose main focus was to evaluate new fall detection algorithm and to demonstrate the feasibility of individual calibration. With the information provided by the ADL classification, individual calibration algorithm was successfully carried out in the current study. As explained in Chapter 3, the ADL classification function is allocated in the non real-time processing module (see chapter 3), and hence the IAM framework neither dictates nor restrict the choice of ADL classification algorithm. In future studies and other practical applications, arbitrary complex and resource-consuming ADL algorithms can be implemented, and interfacing with individual calibration function can be easily made. One of promising ADL classification algorithms that will be considered in the future is the wavelet techniques (Najafi, et al., 2003) with only one sensor configuration. This is to consider the overall detection performance and the user compliance. The concept of adopting different analytical techniques for detecting different types of ADLs (Mathie, Celler, et al., 2004) may also be considered in designing a new ADL classification algorithm. In terms of testing procedure, it is advised to adopt less controlled activity protocol in a semi-naturalistic environment (Bao, 2003) in the future. One idea would be to have the participants move freely in a semi-living environment and to have their motion features monitored continuously without interruption for a period of time.

5.8.2. Performance of individual calibration

One important way of improving fall detection performance is to adopt an individualized detection threshold (*TH*). As stated in the introduction section (Chapter 1), one of the major factors responsible for misdetection and false alarms is the heterogeneity of between-subject motion characteristics, which make it difficult for a generic *TH* to achieve optimal performance at an individual level. Though seemly attractive, the traditional way to conduct individual calibration is facing practical constraints because it is a supervised process and requires a dedicated facility (Sekine, et al., 2000). Recognizing such constraints, the current study implemented an IAM framework, which made it possible to perform individual calibration and thereby to obtain individualized *TH* automatically.

In the current study, the idea of individual calibration was based on the relationship between *TH* and two of the detection performance measures (sensitivity and specificity). As discussed in Study 1, changes in *TH* were found to be associated with changes in specificity in the same direction but changes in sensitivity in the opposite direction. For each individual, the current calibration algorithm returned an updated *TH* which was either higher or the same as the generic *TH* while maintaining a desirable level of specificity. Therefore, it was expected that in the current study the fall detection algorithm with the individualized *TH* would result in improved sensitivity and reduced response time, compared to the one with generic *TH*.

The findings from the current study demonstrated that with the IAM framework, it was feasible to carry out individual calibration automatically, without an explicit and supervised calibration process during the data measurement. As indicated in Table 15, individualized *THs* were obtained for 4 out of 10 participants in the current study. This was expected because on one hand, the generic *TH* can be considered, conceptually, as a 'balanced' choice among a group of individualized *TH*s. Therefore, an individual's *TH* may be higher or lower than the generic *TH*. On the other hand, the current individual calibration algorithm was designed in such a way that it would only return an individualized *TH* that was higher than the generic *TH*. The rationale behind this logic is that the detection performance when an algorithm adopts a *TH* higher than the generic *TH* is predictable. For that individual, the sensitivity of the algorithm will at least remain the same, if not increase, while the specificity remains the same. On the contrary, the detection performance when an algorithm adopts a *TH* lower than the generic *TH* is unpredictable. For that individual, even though the specificity associated with the lower *TH* may increase, the corresponding sensitivity may decrease to a level that would render the entire fall detection algorithm useless in detecting fall events for that individual. Therefore, individualized *TH*s would not be lower than the generic *TH* for all the participants.

Despite the feasibility to compute and adopt individualized *TH*, the effect of the individual calibration on the fall detection performances was not substantial in the current study. Both sensitivity and specificity were found to remain approximately the same for algorithms with and without individualized *TH*. Even though the response time from the algorithm with individualized *TH* was statistically lower than that from the algorithm without, the reduction in response time due to the individual calibration was found to be 2.4% or 6ms in average. To the author's knowledge, the only study that adopted an individual calibration technique was conducted by Sekine et al. (2000). Even though Sekine's study focused on classifying walking patterns using individual-specific thresholds and no comments were available as to the effect of adopting individual calibration, the individual-specific thresholds were considered critical in their classification algorithm.

The small benefits offered by the individual calibration may be explained from three aspects. First, it may be due to the so-called ceiling effect. In the current study, the sensitivity of the algorithm without the individualized *TH* was already the maximum (100%). This left no room for further performance increase in the current study. Second, it may be due to the fact that the actual detectable falling activity was an extremely rapid process. Even though for some participants, it appeared that the individualized *TH* was dramatically reduced comparing to the generic *TH*, the reduction in response time was not obvious. Third, due to the extensive screening criteria, the participants in the current study represented a more homogenous population than the general elderly. It may be possible that the effect of the individual calibration on fall detection would be greater for a more diverse participant group in the future study.

Given the findings from the current study, the utility of individual calibration is questionable. Consequently, the inclusion of the IAM framework in fall event detection may not be necessary. On the bright side, the individual calibration did not negatively impact the overall detection performance. On the dark side, from a practical perspective, it may be argued that the small performance improvement does not justify the hardware and computational resource expenditures associated with adding individual calibration processing module (and a complex ADL classification module). In addition, the user compliance of a fall detection system without the non-real-time processing module is also likely to be enhanced. Nevertheless, the authors would not deny the possibility that the benefits of individual calibration may become more visible with a refined calibration algorithm or a large number of fall trials in future studies.

5.8.3. Performance of fall detection

Fall event detection is an important fall intervention solution as it helps reducing the fall-related injuries in an indirect manner. Currently, the major benefit offered by various fall event detectors is to ensure the timely arrival of remote medical assistance without or with minimal human intervention, thereby indirectly reducing the impact-related complications and mortalities (Nyan, Tay, Tan, et al., 2006). Moreover, the prior-to-impact type of fall event detection which is the focus of the current study, is an essential component for a prospective on-demand fall injury prevention system (Wu, 2000), which may directly prevent the physical injury associated with fall accidents. Therefore, a prior-to-impact type of fall detection algorithm was developed and evaluated in the current study and was hypothesized to provide detection performance superior to those existing research.

The findings from the current study indicated that the new algorithm achieved a high detection performance in terms of sensitivity and specificity. Such performance was also validated by the validation dataset. As discussed in Study 1, both sensitivity and specificity are very important quantitative performance measures to evaluate the effectiveness of a fall detection algorithm. Hence, these two measures were reported in most of the previous studies (Table 16). The performance of the new algorithm in the current study compared favorably to those in the literature (Table 16). The research conducted by Nyan et al. (2006) was the only prior-to-impact fall detection study in the literature. Therefore, the performance of the ω-based algorithm in their research was taken for comparison. Specifically, the new algorithm had a lower specificity (95.65% vs. 97.5%) but the same level of sensitivity (100%) compared to the ω-based algorithm.

Table 16 – Summary of fall detection studies

Authors	Year	Detection algorithm: Object of detection	Detection algorithm: Measurement	Fall testing protocol: Participants	Fall testing protocol: Types of fall	Performance measures: Sensitivity	Performance measures: Specificity	Performance measures: Timing
Williams et al.	1998	Impact & Post-impact	Impact sensor; tilt sensor					
Doughty et al.	2000	Impact & Post-impact	Impact sensor; tilt sensor	Mannequin	5 types[1]	N/A		
Noury et al.	2000	Impact & Post-impact	Accelerometer; tilt switch; vibration detector					
Noury et al.	2003	Post-impact	Accelerometer	10 young	3 types[2]	83%	79%	
Degen et al.	2003	Post-impact	Accelerometer	1 young	3 types[3]	65%[3]		
Hwang et al.	2004	Post-impact	Accelerometer, gyroscope, tilt sensor	3 young	3 types[4]	96.7%		
Diaz et al.	2004	Impact	Accelerometer	8 young	Horizontal	89.6%	60.0%	
Lindemann et al.	2005	Post-impact	Accelerometer	1 young & 1 elderly	7 types[5]	100%		
Karantonis et al.	2006	Post-impact	Accelerometer	6 young	3 types	100%		
Nyan et al.	2006	Post-impact	Accelerometer					
Nyan et al.	2006	Prior-impact	Gyroscope	10 young	3 types[4]	100%	92.5% ~ 97.5%	98~220ms[7] (lead time)
Bourke et al.	2007	Impact	Accelerometer	10 young	8 types[6]	100%	100%	
CURRENT STUDY	2008	Prior-impact	Accelerometer, gyroscope	10 elderly	Backward	92.31%	97.04%	274ms (response time)

[1] Forward fall with knee flex and knee rigid, backward fall, sideway fall, fall downstairs

[2] Backward fall, forward fall, and Syncopa

[3] Forward fall, backward fall, and sideway fall, with success rate to be 100%, 58%, and 45%, respectively; overall rate = 65%

[4] Forward fall, backward fall, and sideway fall

[5] Forward fall, sideway fall, backward fall with and without hip flexion, backward fall against a wall, imitation of a collapse, and fall while picking up an object

[6] Forward, sideway to left and right, backward fall, all with and without knee flexion

[7] Lead time for forward fall, sideway fall and backward fall is 200~210ms, 135~182ms, and ~98ms, respectively.

Such direct comparison, however, is not conclusive for the following reasons. First, are the differences because of the way backward falls were induced? In the previous study (Nyan, Tay, Tan, et al., 2006), the participants fell from a standing posture while in the current study, the participants fell during normal walking. Thus, it is very likely that the motion dynamics of these two types of falls are different (Nyan, Tay, Tan, et al., 2006), which may influence the performance of a given fall detection algorithm. Second, are the differences in motion characteristics between the younger adults (as in previous study) and the older adults (as in the current study) during a fall? In addition, it is plausible that the pneumatic actuator used to induce the backward falls in the previous study may artificially induce additional rotational motion to the participants. Such additional motion is likely to make fall activities more distinguishable from ADLs.

Therefore, the current study also evaluated a baseline algorithm which was adopted exactly as the ω-based algorithm from the previous study (Nyan, Tay, Tan, et al., 2006). It was found that the new algorithm performed considerably better than the baseline algorithm with 14.29% increase in sensitivity, and 5% increase in specificity. In addition, the performance of the baseline algorithm in the current study was much worse than those reported in literature (Nyan, Tay, Tan, et al., 2006). For example, in contrast to the ideal sensitivity (100%) of the ω-based algorithm, the baseline algorithm in the current study achieved the sensitivity of only 83.33%. In light of such performance differences of the same algorithm, it was concluded that differences in testing protocol and testing participants may likely contribute considerably to the detection performance of a given detection algorithm. Furthermore, it was recommended that any fall detection algorithm should be evaluated in versatile scenarios to fully comprehend its capability.

The new algorithm was also found to be able to detect the fall event prior to the impact successfully, with an average response time to be 255ms. Response time or lead time (which can be obtained by subtracting the response time from the entire time of fall) has great implications in designing an on-demand injury protection system. Being able to detect falls faster (shorter response time) or in other words, being able to provide more time (longer lead time) for a protection system to function before the fall impact occurs is very critical for an active fall protection system to prevent/reduce impact-related injuries. Due to the testing constraints, no actual fall impact was available in the current study. Thus, the precise lead time was also not available for the current study.

To facilitate the comparison with results from literature, the lead time in the current study was estimated by two methods (Figure 29). First was to assume the average time for an entire fall activity. It was reported that an entire fall activity took about 2.1s (Nyan, Tay, Tan, et al., 2006). Given that such duration is composed of response time and lead time, the estimated lead time in the current study would be about 1845ms, which is much longer than the reported lead time (98ms) for a backward fall (Nyan, Tay, Tan, et al., 2006). It should be noted that such estimation is subject to several sources of errors including: 1) inconsistent definition of the starting point of the fall activity; 2) different ways of inducing falls (slip-induced backward falls vs. pneumatically-activated fall from standing).

The second method to estimate the lead time was to assume the average lead time provided by the baseline algorithm in the current study. Because the baseline algorithm in the current study was adopted from the ω-based algorithm in the literature (Nyan, Tay, Tan, et al., 2006), it can be assumed that the lead time of the baseline algorithm was in average 98ms. Considering the response time of the new algorithm was in average 35ms less than that of the baseline algorithm, the lead time for the new algorithm in the current study can be estimated as 133ms. Similarly, this method of estimation is also subject to several sources of error including: 1) differences in falling dynamics between participants (elderly vs. young); and 2) different ways of inducing falls. The results from these two ways of estimation are dramatically different (1845ms vs. 133ms). Nevertheless, it can be concluded that the new algorithm in the current study is able to detect backward falls considerably faster than the existing algorithms and thus allows for more lead time.

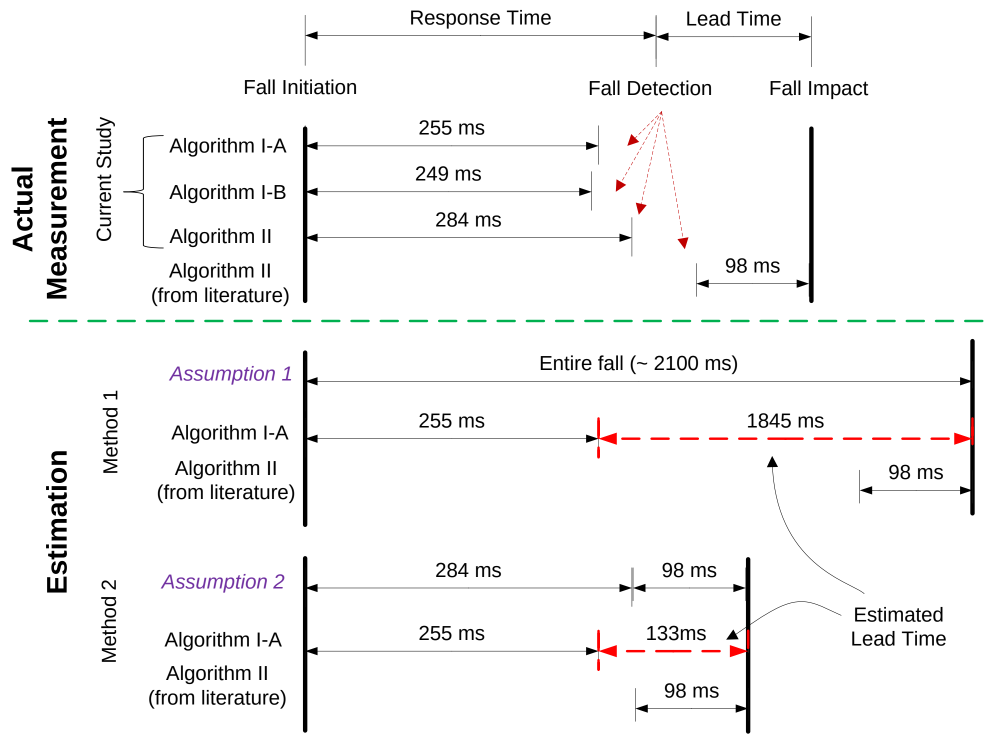


Figure 29 – Comparison of measured response time (current study), measured lead time (literature), and estimated lead time (based on the results from current study) during backward fall. Estimation method 1 assumes an entire fall to be ~2100ms. Estimate method 2 assumes the fall detection events coincide between current study and literature (Nyan, Tay, Tan, et al., 2006).

The performance improvements of the new algorithm over the baseline algorithm can be attributed to the unique design of the new algorithm which utilized two-dimensional information. As discussed in Chapter 3, the controlled way of executing an ADL activity by an individual is not only reflected in controlling the motion intensity, but also in controlling the body posture. This is the basis for the new algorithm to utilize trunk angular velocity and trunk angle simultaneously. Previous studies have also employed a multi-criteria algorithm to detect a fall. For example, Lindemann et al. (2005) developed a 3-criteria algorithm by which a fall was detected if: 1) the sum-vector of acceleration in transverse plane was higher than 2g; and 2) the calculated velocity right before initial contact was higher than 0.7m/s; or 3) the resultant vector of acceleration was higher than 6g. Hwang et al. (2004) designed an algorithm using three types of measurements: acceleration, angular rate, and orientation tilt. A fall was detected if: 1) body tilt was above Threshold 1; and 2) the range of acceleration was above Threshold 2; and 3) the peak acceleration was above Threshold 3. Nevertheless, previous studies only processed the multi-dimensional measurements discretely, in a way that multiple one-dimensional measurements were processed either in a sequential manner, or in a parallel manner. On the contrary, the two-dimensional measurements in the current study were utilized in an integrative manner. All the information was analyzed in one discriminant function to generate one processed signal to be compared against one detection threshold.

Beside the detection performance improvements, the current study also has several methodological advantages over the previous studies. First of all, the elderly participants, instead of the young adults, were involved in the fall testing protocol in the current study. As summarized in Table 16, most of previous studies only involved healthy young adults for testing due to the safety concerns. The elderly population, however, is most likely the intended users for such fall detection devices. As reported in the literature (Hsiao & Robinovitch, 1998; Lajoie, Teasdale, Bard, & Fleury, 1996), the motion characteristics between young and elderly populations are expected to be different. For example, the elderly were found to be slower when performing ADLs (Lajoie, et al., 1996), and took longer reaction time to prevent them from falling (Hsiao & Robinovitch, 1998). Therefore, generalization of the testing results obtained from young participants to the elderly population has to be made with caution. Besides, the results from the current study have suggested that different testing participants were likely to be a major source of error in explaining the different detection performances of the same detection algorithm.

Second, the current study induced slip-induced backward falls during walking. For most of the previous studies (Bourke, et al., 2007b; Karantonis, et al., 2006; Lindemann, et al., 2005), various types of falls were performed by the participants voluntarily from standing posture. More recently, involuntary falls were induced but still from standing posture (Nyan, Tay, Tan, et al., 2006). The current study represents the first attempt to evaluate an algorithm in falls initiated during dynamic activity. Such investigation is considered to be valuable because most fall accidents occurred while the older adults were in motion.

Third, the new algorithm developed in the current study was shown to be able to detect fall events prior to the fall impact. Most of algorithms in the previous studies (Table 16) were only capable to detect a fall after the individual landed on the ground. As valuable as being a fall alarming system, such algorithms could not be implemented in an on-demand injury protection system, which in the author's opinion may offer a breakthrough in reducing fall-related injuries.

5.8.4. Limitations

The current study was facing two major limitations, in terms of limited types of fall being tested and measurement of incomplete fall dynamics.

The new fall detection algorithm was designed for and evaluated with the slip-induced backward falls only. The backward falls were chosen in the current study mainly due to the fact that slipping was considered the most frequent unforeseen triggering event leading to majority of the falls on the same level (Swedish Work Environment Authority and Statistics Sweden, 2000). As summarized in Table 10, the algorithms from the previous studies were usually designed for multiple types of falls, which may include forward falls, backward falls, sideway falls, collapse from standing, and etc. It is certainly desirable for a detection algorithm to be able to detect as many different types of falls as possible. As explained in Chapter 1, the current study represented the first step towards designing a comprehensive fall detection algorithm. Furthermore, the methodology utilized in the current study can be easily adapted to design other algorithms that are capable to handle more types of fall in the future.

The fall dynamics of the backward falls measured in the current study was not complete. For the safety of the participants, the backward falls were stopped by the overhead harness prior to the impact on the floor. On the contrary, participants in the previous studies were usually allowed to completely fall on the floor (protected by cushions like mattress) (Bourke, et al., 2007b; Karantonis, et al., 2006; Nyan, Tay, Tan, et al., 2006). There are two major disadvantages associated with this limitation. First, the fall detection algorithms can only be evaluated during part of the backward fall dynamics. For those fall trials that were not successfully detected by the algorithms in the current study, it was unknown whether they would be detected in the later phase of the falls. It was possible that in practice, the new fall detection algorithm may be able to detect more falls other than in the lab environment. The limitation in measuring a complete fall trial may also contribute to the poor performance of the baseline algorithm, which may be capable to detect more falls in the later stage of the fall dynamics. The second disadvantage is that the measurement of lead time was not feasible. Because participants were not allowed to fall on the ground, the duration for an entire slip-induced fall activity could not be measured in the current study.

The above limitation, however, also offers two advantages over previous studies. First, the use of overhead harness made it possible to involve elderly participant in the testing. Almost all the previous studies hesitated to involve elderly in fall testing (Table 16). Their major concern was whether it would be safe to subject elderly participants to the impact on the ground, regardless of the cushioning. In the current study, however, the safety of the elderly was assured because no direct impact on the ground was allowed. Second, utilizing an overhead harness system made it possible to measure falls in motion, which was considered a big step forward relative to falls from a standing posture as in the previous studies (Bourke, et al., 2007b; Karantonis, et al., 2006; Nyan, Tay, Tan, et al., 2006). In summary, the limitation with incomplete measurement of fall dynamics was a compromise to increase the external validity of the fall detection algorithm. It is certainly desirable to measure the complete fall dynamics in the future studies if advanced testing instruments and procedures are available.

As a proof of concept investigation, the current study was also associated with various other limitations and simplifications. First, the current study involved limited sample size and healthy older adults only. Future studies involving larger sample size and diverse participant populations would further enhance the external validity of the new fall detection algorithm. However, it may be infeasible to expose any frail elderly or patients to fall perturbation even though there will not any impact to the ground. Therefore, it is advised to experiment with the younger and the middle-aged adults to investigate the effect of diverse participant population. Second, all the measurements were off-lined processed and analyzed in a local computer. The next step would be to construct a prototype fall detection system with data buffering and on-line processing capability. Future investigations of the effectiveness of such a prototype system in both laboratory and actual living environment would be necessary towards practical applications.

5.8.5. Future studies

In terms of fall event detection, future studies can be done in several directions. First is to adapt the methodology utilized in the current study to develop algorithms for more types of falls. It is expected that the unique motion features of different types of falls may also be reflected in the trunk angular phase plots. Second is to develop an innovative fall testing paradigm which allows the investigation of a complete fall dynamics and the protection of the human participants. Third is to involve greater sample size and more diverse participant populations. Considering the risk imposed on the frail elderly or patients, it may be reasonable to involve younger and middle-aged participants into testing first. The effectiveness of the individual calibration function can also be further explored with such a diverse population.

Last but not the least, the a priori probability of the fall occurrence in one's daily life has to be investigated. Meanwhile, the relative costs associated with misdetection and false alarms have to be quantified. This information is necessary to construct an optimal algorithm configuration when the compromise has to be reached between reducing misdetection and reducing false alarms.

In terms of external validity, one important research idea in the future is to design a less controlled ADL testing protocol so as to be more faithfully representative of the real-world scenarios. A complete field testing with a prototype system would certainly be the ultimate goal. But as an immediate follow-up study, it is advised to design a continuous testing protocol in a semi-naturalistic environment as a compromise between experimental control and real-world practicality.

Beyond fall event detection, several other research ideas may stem from the current study. For example, though the utility of IAM framework in fall detection applications (via automatic individual calibration) was not substantial, the current study did demonstrate the feasibility of this framework. As explain in Chapter 1, the IAM framework can also be used in designing an activity monitor for epidemiology research, and in developing a stability monitor for long-term fall risk assessment. Therefore, various application scenarios of the IAM framework will be explored in the future.

5.8.6. Application potentials of the findings

The findings from this dissertation can be applied to build a protective airbag system. The estimated lead time (133 ms) is considered to be sufficient to deploy an airbag, which typically only requires 50ms to inflate (Chan, 2000). As demonstrated by a prototype protective system (Fukaya & Uchida, 2008), the technology of the personal airbag system is feasible. What is lacking, as the authors put it, is the design of the fall event trigger system. Therefore, the knowledge from this dissertation can be extremely useful in terms of designing a complete on-demand protection system to reduce the physical injuries associated with falls.

5.8.7. Conclusions

In conclusion, the new algorithm was successfully developed in the current study and was able to achieve an excellent fall detection performance, in terms of sensitivity and specificity. The new algorithm was also able to detect the slip-induced backward falls prior to the impact. In addition, the individual calibration was executed successfully. Though statistically significant, the detection performance enhancement offered by the individual calibration was negligible, which made its utility questionable in practice.

APPENDIX A – IRB FORM

CONSENT DOCUMENT FOR PARTICIPANTS IN RESEARCH PROECTS INVOLVING HUMAN SUBECTS

Locomotion Research Laboratory
Virginia Polytechnic Institute and State University

TITLE OF PROECT: Biomechanical Analysis of Slip-Induced Falls and Activities of Daily Living

PRINCIPAL INVESTIGATOR: Thurmon E. Lockhart Ph.D., Grado Department of Industrial and Systems Engineering, Virginia Tech

I.

Purpose of this Research Project

Older adults are at a higher risk of falls due to the way they walk and problems with their posture. They face a greater risk when walking on slippery surfaces. More than 25% of older adults fall every year, with emergency departments treating more than 1.6 million seniors due to fall-related injuries annually, resulting in the hospitalization of 373,000.

The purpose of this study is to evaluate, through computerized imaging of human body movements, the body motion characteristics associated with everyday activities of younger and older adults (such as walking, sitting, standing, stooping, lying down), as well as body motions associated with and leading to slip-induced fall accidents. To achieve some of the experimental objectives, a fall detection monitor will be tested. Fall event detectors are used as an alarm system for the elderly who live alone, and can summon emergency assistance should the individual be unable to reach or use the telephone. In order to design an effective fall event detection system, suited to the unique daily activities and movements of the elderly, this study will develop a mathematical model to differentiate between slip and fall accidents and normal, routine daily activities, helping to reduce false alarms generated by the fall detector.

II. Procedures and Project Information

A. Participant Selection

Solicitation and Selection of Study Participants -A total of fifty (50) young adult and elderly individuals in two age groups, 18-35 and 65-85 years will be enrolled and participate in this study.

Inclusion Criteria – To be considered for this study, you must be an adult, in the 18-35 or

65-85 year age groups, with none of the exclusionary criteria listed below.

Exclusion Criteria – If you have any of the following problems or conditions, you will not be allowed to participate in the study:

·

The following bone and joint problems: osteoporosis; previous knee or hipreplacement; previous ankle or shoulder surgery; moderate to severe arthritis; routine back or neck pain; previous surgery on the vertebrae of the neck or lumbar spine; previous knee surgery for cranial cruciate ligament repair; knee ligament problems that have not been surgically repaired; fallen arch(es) - flat feet

·

The following neurological problems: previous stroke resulting in weakness of one or both legs; Parkinson's disease; pinched spinal nerves causing pain or affecting gait; previous history of a detached retina.

·

The following muscle problems: persistent muscle weakness; muscle wasting conditions; unrepaired inguinal hernia.

·

The following cardiovascular problems: tires easily and has difficulty breathing upon normal walking; congestive heart failure; cardiomyopathy (enlarged heart); uncorrected aortic aneurysm; circulatory deficiencies in the feet associated with chronic diabetes; hemophilia; taking significant doses of anticoagulants

B. Time Requirements

You will be asked to come the lab for three separate sessions, spending approximately one hour during each of the sessions, for a total study participation time of three hours. You may decide, if you physically able, to combine sessions: (1) performing the first and second sessions on one day, and performing the third session on a second day; (2) performing the first session on one day, and performing the second and third sessions on a second day; or (3) performing the first, second, and third sessions on three separate days.

C. Study Procedures

First Session

On the first day, during the consent process, we will describe what you will be doing in the experiment, show you the equipment you will be wearing, and let you walk on the experimental track. You will undergo a general physical examination by the study physician, to review your health history form, and to assess the flexibility of your joints and range of motion of your limbs. If it is determined that you have any of the exclusionary criteria, or that you have some other pre-existing condition of concern to the physician which would adversely affect the experimental data collection, you will be thank and excused from the study, and will be provided with $10 compensation for your participation to that point.

You will then be given an opportunity to walk around the laboratory wearing the safety harness, to allow familiarization with the equipment (e.g., the harness and fall-arresting rig) and the normal floor surface on the "track". The harness system is designed to protect you during the slip and fall experiments. The fall arresting rig will only allow you to fall 20 cm or less, preventing you from falling to the floor. You may feel a small jerk in your torso as the harness stops your fall.

Second Session

During the second session, you will be asked to change your clothes in a private change room, where you will put on clothes that we will supply you (e.g., black tank top and shorts). During this session, we will have you wear normal lab supplied shoes (sneakers).

At this time, retro-reflectors (white styrofoam balls similar to ping-pong balls) will be attached, to the laboratory-supplied clothing that you are wearing, over anatomically significant locations on your body, such as your joints. Retro-reflectors will be placed over the joints of the ankle, knee, hip, shoulder, elbow and wrist, as well as on the toes of each foot, calf and thigh of the legs, pelvis, and head plus trunk markers over the 10th thoracic and 7th cervical vertebrae and sternum (breastbone) to assess your body and joint movements. This will allow us to create computerized stick figure models of your movements during the experiment. To address modesty or cultural concerns, you will be given the choice of having someone of the same gender to affix the retro-reflectors to their garments/body.

We will also attach 2 to 4 Inertial Motion Units (IMUs) to belts over your sternum, lower back, wrist, or thigh, with one unit per anatomic location. To address modesty or cultural concerns, you will be given the choice of having someone of the same gender to affix the IMUs. We will ask you which of your feet is your dominant ("kicking") foot.

First Experimental Component – Baseline

Wearing either the normal lab shoes, you will be asked to walk back and forth along the test track" for 15 minutes. At both ends of the track, there will be a station where you will receive written instructions directing you to perform specified filing tasks, e.g., separate 4 blue pieces of paper and file them. You will also receive written instructions to look at the TV screen at the opposite end of the track, as you are walking to that end, to count the number of dots on the screen of a certain color. When you reach that end of the track, you will be asked to tell how many you observed. You may be supplied with a Walkman audio player during the walking experiment, playing old comedy routines, to conceal any noises associated with laboratory activities. If you become tired during walking, please let the lab staff know that you would like to stop and rest. Or if you wish to withdraw from the study, you may request to do so.

Second Experimental Component – Slippery Conditions

During the next 15 minute session, you will conduct similar filing tasks as described above. At two random time points, the researchers will, without your knowledge, create a slippery condition on the track. You will slip, but as mentioned previously, the harness will prevent you from falling to the floor. You may experience a jerk in the shoulders and neck as the harness prevents your fall. If you become tired during walking, please let the lab staff know that you would like to stop and rest. Or if you wish to withdraw from the study, you may request to do so.

If you choose not to continue on to the third session on this day, you will, at the conclusion of the test, change back into your personal clothes, and will be paid for your participation in this session. If you decide, and are permitted to continue on to the third session on the same day, you will remain in the lab supplied garments with the retro-reflectors and IMUs attached.

Third Session

If you elected to participate in the third session on a separate day, you will change into the lab-supplied clothing and have the retro-reflectors and IMUs attached as described in the Second Session. If you elected to continue from the Second Session to the Third Session on the same day, you will already be appropriately dressed and instrumented. You will not be wearing the harness in this session.

You will be asked to perform a variety of tasks to assess your movement. You will be asked to sit down on an exam table, and then to stand up from your sitting position. You will be asked to lie down on your back on the exam table, and then to rise up to a sitting position. You will be asked to bend over, from a standing position, to pick up a coin or other object from the floor. Your movements will be monitored/recorded by an infrared camera used to detect movements of the retro-reflectors, so that we can create computerized stick figure models of your movements during the experiment. The camera will not yield images from which your likeness would be identified. At the conclusion of this session, you will change back into your personal clothes, and will be paid for your participation in this session.

At least two graduate research assistants will be present during all testing periods. Staff members running the tests will strongly emphasize, in both spoken and written instructions, that you are free to discontinue participation at any time. All lab-supplied garments that you will wear will be laundered after each use, with all subjects provided with clean, laundered garments.

III. Risks Involved in Participation

While this study involves the use of safety equipment to prevent contact with the floor during an experimentally induced slip or fall, it does involve more than minimal risk for individuals with bone, joint, or muscle problems. For that reason, individuals with any of the exclusionary criteria have been excluded from the study.

You might encounter the following risks during your participation:

Emotional – You may feel disappointment or self-doubt in not being as agile as when you were a younger age. You may feel embarrassed at what you perceive as a "poor performance".

Physical – You could experience minor muscle sprain (similar to those encountered in regular daily activities), joint pain (shoulder, knee, ankle), or neck sprain. To minimize injuries, you will be wearing a fall arresting rig and harness system to protect you from harm caused by slips and falls. Prior to your participation, the harness system will be adjusted to your individual height, ensuring that falls are limited to 20 cm or less limiting the downward and forward progression of your body to reduce physical risks noted above. The experiment will be terminated if one of the following conditions occurs: if you decide to discontinue participation; or, you experience any pain in the back, knees or ankles following walking or slipping. Potential participants will be excluded if bone or joint problems are present that would make participation unsafe or which would compromise the integrity of the research results.

Over 120 human subjects have been tested using the walking surfaces and safety harness, and to date, no injuries have occurred. However, in the event that you are injured while participating in the study, you will be responsible for any expense associated with emergency medical treatment, as neither the researchers nor the University have money set aside for medical treatment expenses.

IV. Benefits from Participation

You are not promised any specific/direct benefits for your participation in this study. The results of this study may yield benefits to adults and seniors through development of recommendations for education on slip and fall prevention.

V. Extent of Anonymity and Confidentiality

You will be assigned a unique individual code number. The code number will be used on all of your study documents and data files. The Principal Investigator (PI), Dr. Lockhart, will maintain a code key list to link your personal information to the code number used on your data. The code key list will be kept locked in a filing cabinet in the PI's office, and will not be accessible to anyone who is not a project staff member. Coded data will be stored on a computer with password-protected access, and hard copies of data will be kept in a locked filing cabinet in the lab or in the PI's office. At the conclusion of the study, the data will be analyzed, and will be published in scientific journals. You will not be identified in the publications, and your anonymity and confidentiality will be maintained. As required by federal law and Virginia Tech IRB Policy, study records will be maintained for 3 years after the conclusion of the study, after which time they will be destroyed.

Your movements will be monitored/recorded by an infrared camera used to detect movements of the retro-reflectors, so that we can create computerized stick figure models of your movements during the experiment. The camera will not yield images from which your likeness would be identified, only the highlighted white retro-reflectors.

VI. Compensation

Participants enrolled in the study will receive $10 per hour spent in the lab. You will spend 1 hour per session, in three sessions, for a total of 3 hours (and total compensation of $30).
Compensation will be pro-rated. If you withdraw during the first session, you will be compensated $10. If you withdraw during the second session, you will be compensated $10 for the first session and $10 for the second session, for a total of $20. If you withdraw during the third session, you will be compensated in full for each of the three sessions, a total of $30.

VII. Freedom to Withdraw

You are free to withdraw from the study at any time and for any reason. Should the researchers determine that you should be removed from the study, you will be thanked and excused, and provided with pro-rated compensation.

VIII. Subject Responsibilities

You are expected to provide accurate information on your Medical History form. You are expected to adhere to your scheduled participation dates, advising the PI if the date(s) need to be rescheduled, unless you decide to withdraw from the study.

IX. IRB Review of Research

The Virginia Tech Institutional Review Board (IRB) for Projects Involving Human Subjects, has reviewed this proposed study, and has determined that it is in compliance with federal laws and Virginia Tech policies governing the protection of human subjects in research. However, you should recognize that the review does not constitute an endorsement of the research, and that it is up to you to determine whether you are willing to participate in the study after having been informed of the risks, benefits, and procedures involved in this study.

X. Subject / Participant's Permission

I have read the Consent Form and conditions of this project and have discussed it with the research staff or PI. I have had all my questions answered to my satisfaction. I hereby acknowledge the above and give my voluntary consent to participate in this study:

____ Date__________

Subject's Signature

Subject's Project Identification Code: ____________

Should you have any questions about this research or its conduct, research subjects' rights, and whom to contact in the event of a research-related injury to the subject, you may contact:

Thurmon E. Lockhart Principal Investigator

540-231-9088 (office) lockhart@vt.edu (email)

Grado Department of Industrial and Systems Engineering,

Virginia Tech

Blacksburg, VA 24061

David M. Moore 540-231-4991 (office)
moored@vt.edu (e-mail)

Chair, Virginia Tech Institutional Review

Board for the Protection of Human Subjects

Office of Research Compliance

2000 Kraft Drive, Suite 2000 (0497)

Blacksburg, VA 24060

NOTE:

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You must be given a complete copy (or duplicate original) of the signed Consent Document.
.
This Consent document must bear an official IRB date stamp.
Virginia Tech Institutional Review Board: Project No. 07-628

APPENDIX B – MEDICAL HISTORY FORM

Study Title: Biomechanical Analysis of Slip-Induced Falls and Activities of Daily Living
IRB #: 07-628

Date: ________________ **Participant Code Number (ID):** ___________________
Gender:[ ]Male [ ] Female **Age:** _____ **Height (ft/in):** ________ **Weight (lb):** ______
Other Study Specific Measurement(s): ____________________________________
IN CASE OF EMERGENCY CONTACT: **Name:** ___________________**Phone:** ___________

GENERAL INFORMATION		
Do you experience: Shortness of breath [ ] NO [ ] YES Dizziness [ ] NO [ ] YES Headache [ ] NO [ ] YES Easily fatigued [ ] NO [ ] YES Pain in arm, shoulder or chest [ ] NO [ ] YES If Yes was checked, please explain: Are you currently taking prescription or other medication? If so, please list (e.g., for arthritis, pain, bone loss, high blood pressure, immunosuppression, calcium supplements or Fosamax): Have you experienced any slips or falls, and if so, how long ago? Please explain:		
BONE AND JOINTS		
Have you been diagnosed with osteoporosis (thinning of the bones)?	**[ ] NO**	**[ ] YES**
Have you experienced fractures of one or more bones in the past 3 years?	**[ ] NO**	**[ ] YES**
Have you had a DEXA scan (bone scan) done in the past 4 years?	**[ ] NO**	**[ ] YES**
Have you had hip or knee replacement surgery, or ankle surgery?	**[ ] NO**	**[ ] YES**
Do you have arthritis in your hands, knees, ankles, etc.?	**[ ] NO**	**[ ] YES**
Do you have routine back or neck pain?	**[ ] NO**	**[ ] YES**
Have you had surgery on your spine (back) or neck to relieve pain?	**[ ] NO**	**[ ] YES**
Have you had knee ligament problems?	**[ ] NO**	**[ ] YES**

If you had knee problems, was surgery required for treatment?	**[ ] NO**	**[ ] YES**
Do you have a fallen arch (flat foot) in either of your feet?	**[ ] NO**	**[ ] YES**
Have you had long-term shoulder pain or surgery on your shoulder?	**[ ] NO**	**[ ] YES**
BRAIN AND NERVOUS SYSTEM		
Have you ever had a stroke?	**[ ] NO**	**[ ] YES**
If you have had a stroke, has it left you with weakness in an arm or leg?	**[ ] NO**	**[ ] YES**
Do you have Parkinson's disease?	**[ ] NO**	**[ ] YES**
If you have Parkinson's disease, does it affect your balance or walking?	**[ ] NO**	**[ ] YES**
Do you have any inner ear problems causing dizziness or affecting your balance?	**[ ] NO**	**[ ] YES**
Do you have pinched nerves in your spine affecting walking or sensation in your legs?	**[ ] NO**	**[ ] YES**
Are you currently taking any medicines that cause you to be dizzy?	**[ ] NO**	**[ ] YES**
Have you ever had a detached retina in your eye?	**[ ] NO**	**[ ] YES**
MUSCLES		
Do you frequently experience muscle weakness?	**[ ] NO**	**[ ] YES**
Have you been diagnosed with any muscle wasting disease?	**[ ] NO**	**[ ] YES**
Have you ever had an inguinal or other hernia?	**[ ] NO**	**[ ] YES**
If you have had a hernia, was it surgically repaired?	**[ ] NO**	**[ ] YES**
Do you require a cane or a walker to facilitate your walking?	**[ ] NO**	**[ ] YES**
HEART AND CIRCULATORY SYSTEM		
Do you tire easily or get out of breath quickly when walking?	**[ ] NO**	**[ ] YES**
Have you had a heart attack?	**[ ] NO**	**[ ] YES**
Do you have an enlarged heart or congestive heart failure?	**[ ] NO**	**[ ] YES**
Do you have an aortic aneurism that has not been surgically corrected?	**[ ] NO**	**[ ] YES**
Do you have diabetes?	**[ ] NO**	**[ ] YES**
If you have diabetes, have you been told that you have diabetic neuropathy in your feet (affecting sensation or circulation in your feet)?	**[ ] NO**	**[ ] YES**
Do you have hemophilia (inability of your blood to clot)?	**[ ] NO**	**[ ] YES**
Are you taking medicines to thin your blood (e.g., coumadin, heparin)?	**[ ] NO**	**[ ] YES**
SKIN		
Are you allergic to tape, adhesives, or gels used to attach electrodes to your skin?	**[ ] NO**	**[ ] YES**

Have you had any allergic reactions to skin creams or disinfectant solutions applied to the skin (e.g., alcohol, iodine)?	**[ ] NO**	**[ ] YES**

APPENDIX C – PILOT STUDY RESULTS

ADL classification example – STS motion

A pilot study was conducted on two elderly participants. Samples of the methodology and results are provided here, demonstrating the capability of IMU in assessing the ADLs.

Sit-to-stand or stand-to-sit (STS) motion can be detected as the change from sitting posture to standing posture or vice versa (Najafi, et al., 2002). In this preliminary analysis, one tri-axial accelerometer was placed on the low back (close to L5/S1) of the participant. Distinguishing static and dynamic motion was first achieved by applying a filtering technique (Bussmann, Tulen, et al., 1998). Transitions between postures were then identified and trunk motion characteristics during STS became observable.

The participants were instructed to perform the following motions in sequence: stand quietly for about 2s in front of a chair, sit down and relax for 2s, stand up and remain standing quietly for another 2s. The measured raw tri-axial accelerometer signal components and its resultant are illustrated in Figure 30 and Figure 31, respectively.

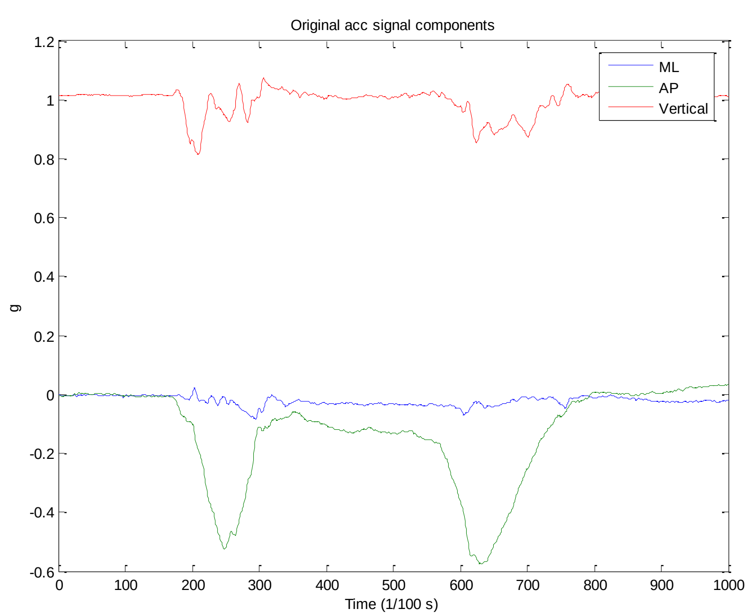

Figure 30 - Raw tri-axial accelerometer signal during STS.
Accelerometer was placed on low back (near L5).

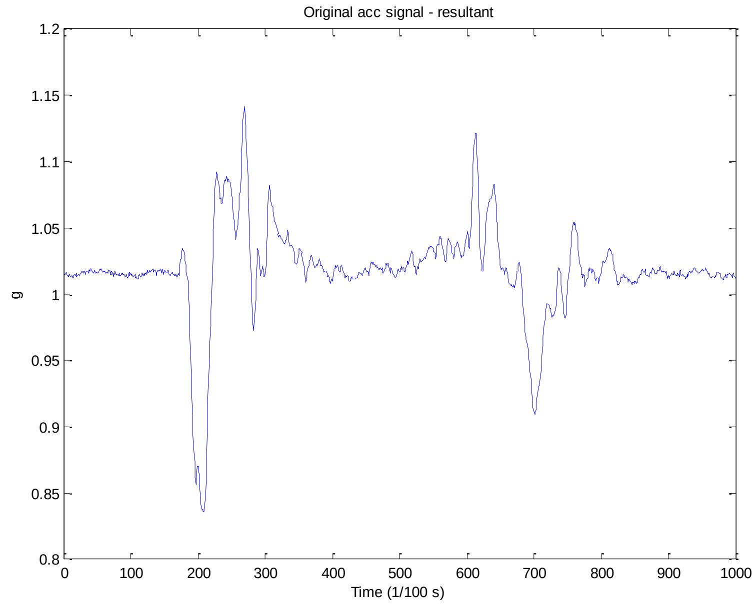

Figure 31 - Resultant of raw accelerometer signal during STS.

Detection of static (posture) and dynamic motion was achieved by applying a high pass filter (Buttworth, 4^{th} order, cut-off = 0.5Hz) to the resultant accelerometer signal. The filtered signal (Figure 32) was compared to the pre-set threshold (0.015g) to detect the static period and dynamic period of motion.

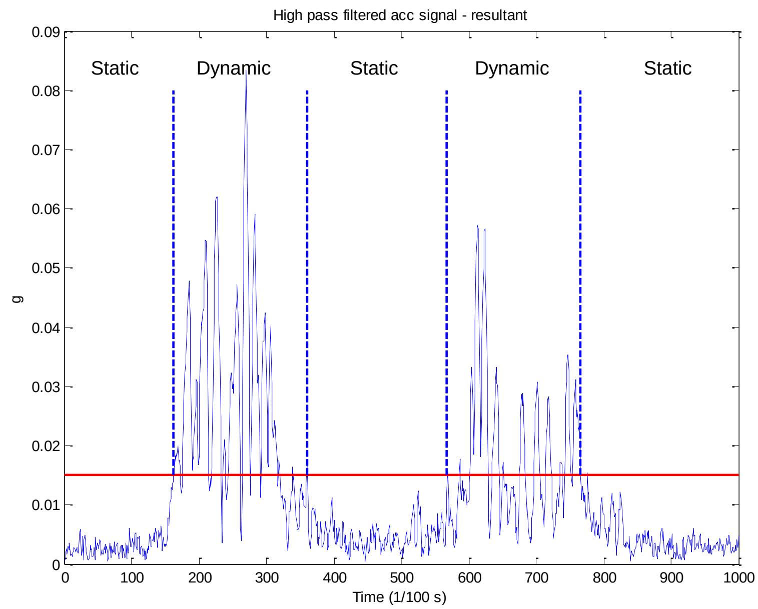

Figure 32 - High pass filtered accelerometer resultant signal during STS

The type of posture can be classified by low-pass filtering the accelerometer signal, which gives the segment orientation. Specifically, to distinguish sitting and standing posture, as few as two accelerometers (one on thigh and one on trunk) can give sufficient information (Bussmann, Tulen, et al., 1998). In this preliminary analysis, since the motion characteristics of the STS transition was of interest, the specific posture was classified from prior knowledge of the study protocol. The accelerometer components were low pass filtered (Butterworth, 4th order, 2Hz) and shown in Figure 33. The trunk sagittal orientation (Figure 34) was successively determined by the vertical and anterior-posterior (AP) components of low pass filtered signal. The characteristic forward trunk rotation during STS transition were observed.

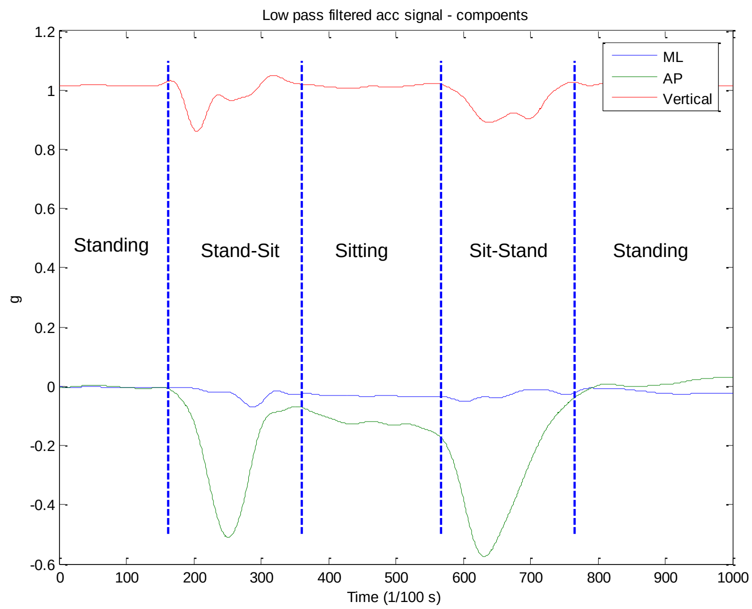

Figure 33 - Low pass filtered accelerometer signal during STS

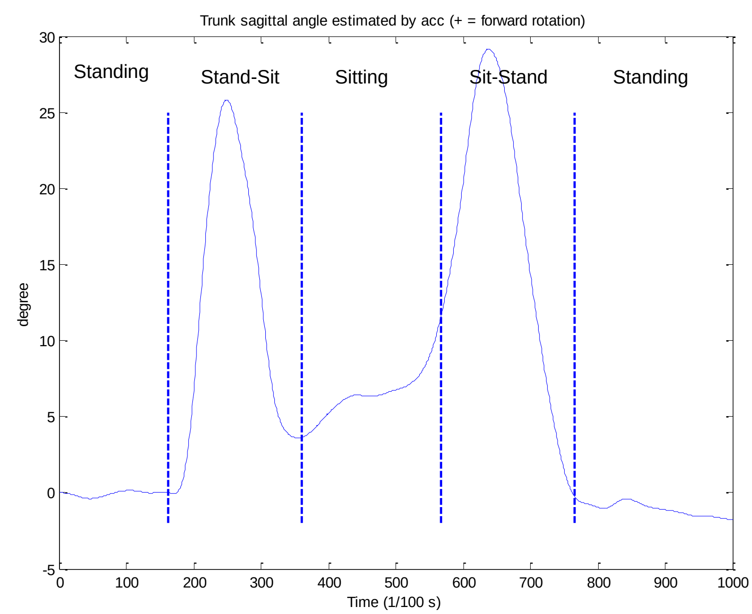

Figure 34 - Trunk sagittal angle during STS

ADL profile of the elderly

Preliminary results were obtained using the data from previous studies. One IMU (MT9-B, Xsens Technology B.V., The Neitherlands) was placed on the back, close to T1 (near the bottom of the neck). Elderly participants were instructed to perform the following daily activities: sitting down, standing up, and bending down to pick up an object from the ground.

The typical phase plot profile from one elderly participant (age = 67, male, weight = 94.5kg, height = 154cm) is shown in Figure 35. It can be seen that the ADLs rarely go far into the first quadrant where considerable backward trunk angle and trunk angular velocity are coupled. It can be speculated that in uncontrolled activities like backward falling, the first quadrant of this phase plot would be occupied. This is, in fact, the case as will be shown in that next section.

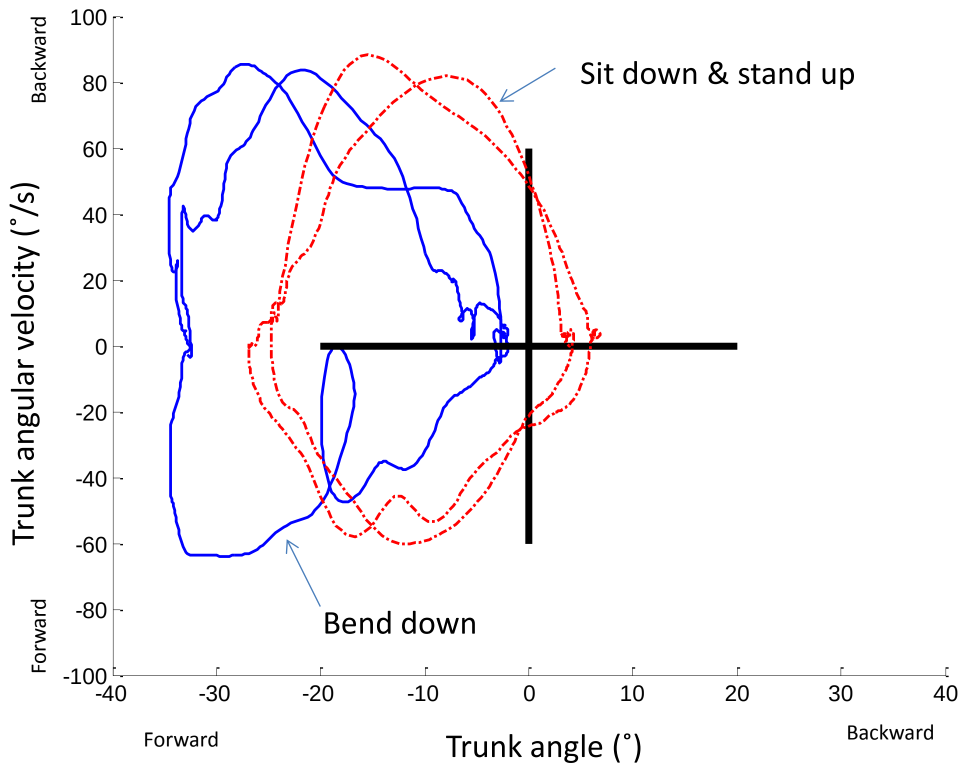

Figure 35 - Phase plot of trunk angular kinematics during STS and bending down motion

Trunk angular kinematics during normal walking and slip-induced falls

Preliminary results were obtained using the data from previous studies. Reflective markers were attached on the trunk segment (L&R_Acronym, L&R_ASIS). An optical motion capture system (ProReflex MCU 240, Qualysis, Gothenburg, Sweden) was used to measure the 3D kinematics of the trunk segments. Walking and slip-induced fall protocols were similar to those described in Chapter 5.

The typical phase plot profile from one elderly participant (age = 65, female, weight =70.9kg, height = 157cm) is shown in Figure 36. A cyclic motion pattern can be seen in the normal walking within a confined angular kinematics region. For the backward falling, however, there was an abrupt, high backward trunk angular velocity exceeding 130˚/s, coupled with a large backward trunk rotation (> 15˚ at the time of peak angular velocity). Compared with the profiles from ADLs (Figure 35), this motion feature of falling was quite distinctive and demonstrated its promising role in serving as the fall detection criteria.

Two detection algorithms were adopted in this dataset to obtain an estimate of the algorithm response time. The first algorithm was based on trunk angle and angular velocity, with the initial threshold set to be (2.8˚, 51.8˚/s). The second algorithm was based on angular velocity, with the threshold to be 130˚/s. The average response time was found to be 141.9ms (SD = 130.3ms) for the first algorithm, and 340.1ms (SD =128.1ms) for the second algorithm.

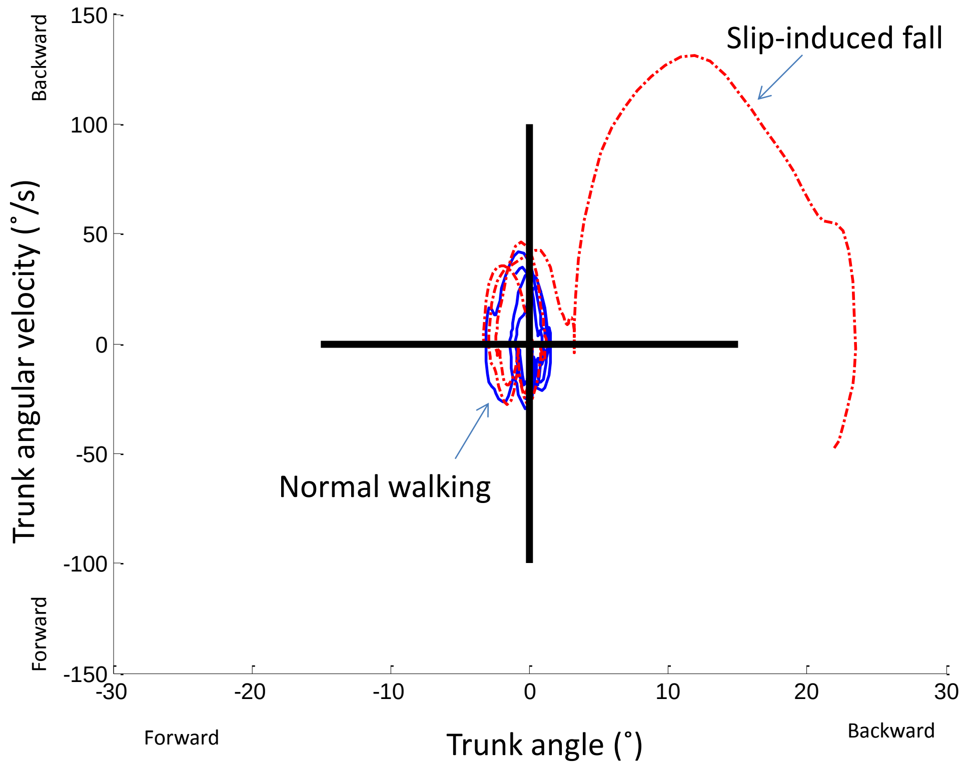

Figure 36 - Phase plot of trunk angular kinematics during normal walking and falling

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