FALL RISK ASSESSMENT BY MEASURING DETERMINANTS OF GAIT

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ABSTRACT

Fall accidents are one of the most serious problems leading to unintentional injuries and fatalities among older adults. However, it is difficult to assess individuals' fall risk and to determine who are at risk of falls and in need of fall interventions. Therefore, this study was motivated by a need to provide a cogent fall risk assessment strategy that may be conducive to various wireless platforms. It aimed at developing a fall risk assessment method for evaluating individuals' fall risk by providing diagnostic modalities associated with gait.

In this study, a "determinants of gait" model was adopted to analyze gait characteristics and associate them with fall risk. As a proof of concept, this study concentrated on slip-induced falls and the slip initiation risks. Two important parameters of determinants of gait, i.e. the pelvic rotation and the knee flexion, were found to be associated with slip initiation severity. This relationship appeared to be capable of differentiating fallers and non-fallers within older adults, as well as differentiating normal walking conditions and constrained walking conditions. Furthermore, this study also leveraged portable wireless sensor techniques and investigated if miniature inertial measurement units could effectively measure the important parameters of determinants of gait, and therefore assess slip and fall risk. Results in this study suggested that pelvic

rotation and knee flexion measured by the inertial measurement units can be used as a substitution of the traditional motion capture system and can assess slip and fall risk with fairly good accuracy.

As a summary, findings of this study filled the knowledge gap about how critical gait characteristics can influence slip and fall risk, and demonstrated a new solution to assess slip and fall risk with low cost and high efficiency.

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1. INTRODUCTION

1.1. Rationale

1.1.1. Background of the current study

Fall accidents are one of the most serious problems leading to unintentional injuries and fatalities (CDC, 2009a). These cause significant pain and suffering to the individual and pose a large economic burden to the society by creating additional medical costs and loss of productivity (Leamon & Murphy, 1995; Roudsari et al., 2005; Stevens et al., 2006). In general, older adults are more prone to falls due to their muscular strength deterioration, gait instability, and sensory degradations (Lockhart et al., 2005). Once they fall, the physical and psychological consequences of falls for older adults are also more devastating than their younger counterparts (Rubenstein, 2006). Therefore, reducing fall accidents, especially among the elderly, has been a major objective of many researchers and healthcare practitioners worldwide.

Numerous fall interventions have been developed and proved effective for preventing or protecting individuals from falling. Examples of common fall interventions include personal protective equipment, balance and gait training, and home hazard modification (Becker et al., 2003; Clemson et al., 2004; Gillespie et al., 2003; Shaw et al., 2003). However, these interventions must be targeted to groups who are at high risk of falling in order to maximize the benefit-cost ratio (Kannus et al., 2005). Also, since most interventions are condition specific to different causes of falls (Gibson, 1987; Gillespie et al., 2003), they need to be selected appropriately before provided to individuals with a specific kind of fall problem. Therefore, targeting recipients and selecting the most appropriate interventions are the two critical challenges that determine the successfulness of any fall intervention program (Rubenstein, 2006). It requires effective fall risk assessment techniques that are capable of: 1) providing valid assessment of an individual's fall risk; and 2) diagnosing the specific causes of falls for this individual.

Unfortunately, existing fall risk assessment methods are far from satisfactory when evaluated by the above two requirements. First, a common way that was used for developing many existing fall risk assessment methods was to correlate the assessments with history of falling (Janice M. Morse, 2006; H. Myers & Nikoletti, 2003; Perell et al., 2001; Scott et al., 2007). In other words, if certain parameters correlated with the number of falls in the past, they were considered as fall risk predictors. The shortcoming of this methodology is that: history of falling is highly dependent on one's activity level. For example, intuitively, a frail older adult has a higher risk of falling. However, if this individual seldom walks, his or her number of falls in the past can possibly be zero. Fall risk assessments developed based on history of falling, therefore, lack validity when one's activity level is not taken into account. Poor validity causes these fall risk assessments to be less reliable, and sometimes even results in conflicting conclusions (Barker et al., 2009). Second, most fall risk assessments are not capable of diagnosing the underlying causes of falls, thus lack of diagnosticity. The lack of diagnostic information makes it difficult to select the most appropriate fall interventions accordingly (Dykes et al., 2009). Therefore, the existing fall risk assessment methods need to be improved.

This study was designed given the above motivation. The main objective of this study was to investigate a new fall risk assessment method with improved validity and diagnosticity. Since slip induced falls accounted for a large portion of fall accidents and could lead to serious hip and head injuries (Courtney et al., 2001; Redfern et al., 2001), this study concentrated on slip induced backward falls as a proof of concept. In the following chapters, the term fall risk refers to slip and fall risk if not specified otherwise.

1.1.2. Framework of this study

In order to develop a fall risk assessment method, the first question to answer is how to define one's fall risk. As analyzed previously, history of falling appears not to be an accurate definition of fall risk because it can be affected by one's activity level. More appropriate metrics to define fall risk are the occurrence and severity of induced falls under a controlled environment. The occurrence of slip and falls is self-explanatory. The severity of slip and falls can be represented by certain severity measures during a slip. Gait studies have suggested that every footstep involves a heel sliding motion (Redfern et al., 2001). It is the sliding heel velocity and the slip distance that differentiates a negligible heel slide (NS), a significant but recoverable slip (SR) and a slip induced fall (SF) (Brady et al., 2000; Lockhart et al., 2003; Redfern et al., 2001; Strandberg & Lanshammar, 1981). Therefore, regardless of the specific thresholds being used in different studies, in general, it is reasonable to define the slip and fall severity based on sliding heel velocity and slip distance, in that faster and longer slips in a controlled environment are associated with higher risk of fall (Moyer et al., 2006).

Although the occurrence and severity of induced slip and falls in a controlled environment can be used to define slip and fall risk, in reality it is the least desirable to assess one's slip and fall risk by actually making him or her fall. Therefore, the next question is naturally raised. Are there certain parameters that are easier to measure and that can be used to predict the occurrence and severity of slip and falls? If such parameters exist, the slip and fall risk assessment can be designed in a less intrusive way. Although such a question can be answered from different perspectives, this study concentrated on the effects of gait characteristics on slip and fall risk because many intrinsic and extrinsic factors affect fall risk by altering gait characteristics (Batterman & Batterman, 2005; Jeffrey Hausdorff, 2005; Redfern et al., 2001; Winter, 1995b). In specific, a "determinants of gait" model was adopted to analyze gait performance. This model was first introduced by Saunders et al. (1953) and it defined six individual determinants of gait (DoGs) for individual ankle, knee and pelvis movements during walking.

The relationship between DoGs and the slip and fall risk can be briefly explained as the following. First, biomechanical analysis has suggested that the whole body center-of-mass (CoM) transits along a significant arched pathway in the plane of progression in a "compass gait" mode which neglects all ankle, knee and pelvis movements during walking. However, in reality, DoGs such as pelvic rotation and knee flexion modify the whole body CoM pathway by flattening CoM arcs and smoothing intersections between consecutive arcs (Inman, 1966; Inman et al., 1981; McMahon, 1984). The flattened and smoothed CoM pathway may reduce CoM vertical velocity, acceleration and jerk in a gait cycle, and can further affect slip and fall risk by changing the friction demand and the slip initiation severity (Lockhart et al., 2003; Pai & Patton, 1997). Since each individual DoG changes the CoM pathway in a unique way, their effects on slip and fall risk may vary as well. By investigating the most important DoGs that are related to slip and fall risk, we could potentially design a slip and fall risk assessment tool by measuring individual DoGs. Furthermore, the decomposition of gait into individual DoGs helps to diagnose underlying gait abnormities (Perry, 1992; Saunders et al., 1953), which could possibly improve the diagnosticity of the fall risk assessment method and facilitate the selection of the most appropriate interventions.

Besides the relationship between DoGs and slip and fall risk, this study also investigated the feasibility of measuring DoGs and assessing slip and fall risk with inertial measurement units (IMUs). In general, IMUs have the major advantages of being light, nonintrusive, inexpensive, and capable of prolonged data collection (K Aminian & Najafi, 2004), therefore appear to be more appropriate for fall risk assessments used in a large scale and free-living conditions.

1.2. Specific Aims and Hypotheses

As analyzed in the previous section, determinants of gait can affect the whole body CoM vertical transition during walking, and the whole body CoM vertical transition may further influence friction demand and slip initiation severity. However, the relationship between DoGs and the slip and fall risk has not been extensively studied. The primary objective of this work, therefore, is to investigate such relationship across different age groups and under different walking conditions. Three studies were designed for this work. Study I analyzed the age related differences in DoGs and the associated slip and fall risk. It illustrated how the DoG method can be used to assess slip and fall risk caused by intrinsic risk factors (i.e. age related gait degradations). Study II investigated the effects of gait constraints on DoGs and the associated slip and fall risk. It illustrated how the DoG method can be used to assess slip and fall risk caused by extrinsic risk factors (i.e. gait constraints). Following that, Study III focused on the design and evaluation of an IMU system for measuring important DoGs and assessing associated slip and fall risk. Specific aims of the three studies and their hypotheses were outlined in the following.

<u>Study I: Determinants of gait in different age groups and the associated slip and fall risk</u>

Specific Aim 1: To analyze differences in determinants of gait between young and old, and investigate how they affect the slip and fall risk

Hypothesis 1-a: Older adults have significantly different DoG parameters than young adults.

Hypothesis 1-b: Older fallers (i.e. older subjects who fell on a controlled slippery surface) have significantly different DoG parameters than older non-fallers (i.e. older subjects who didn't fall on the same slippery surface).

<u>Study II: Effects of gait constraints on determinants of gait and the associated slip and fall risk</u>

Specific Aim 2: To investigate how gait constraints affect determinants of gait and the associated slip and fall risk.

Hypothesis 2-a: The use of knee brace has a significant effect on knee flexion and slip initiation severity measures.

Hypothesis 2-b: The use of arm sling has a significant effect on pelvic rotation and slip initiation severity measures.

Study III: Assessing determinants of gait and the associated slip and fall risk by inertial measurement units

Specific Aim 3: To develop and evaluate an IMU system for measuring important determinants of gait and assess slip and fall risk.

Hypothesis 3-a: IMU measurements for important DoGs are able to differentiate constraint walking and normal walking.

Hypothesis 3-b: IMU measurements for important DoGs are able to differentiate fallers and non-fallers for different age groups.

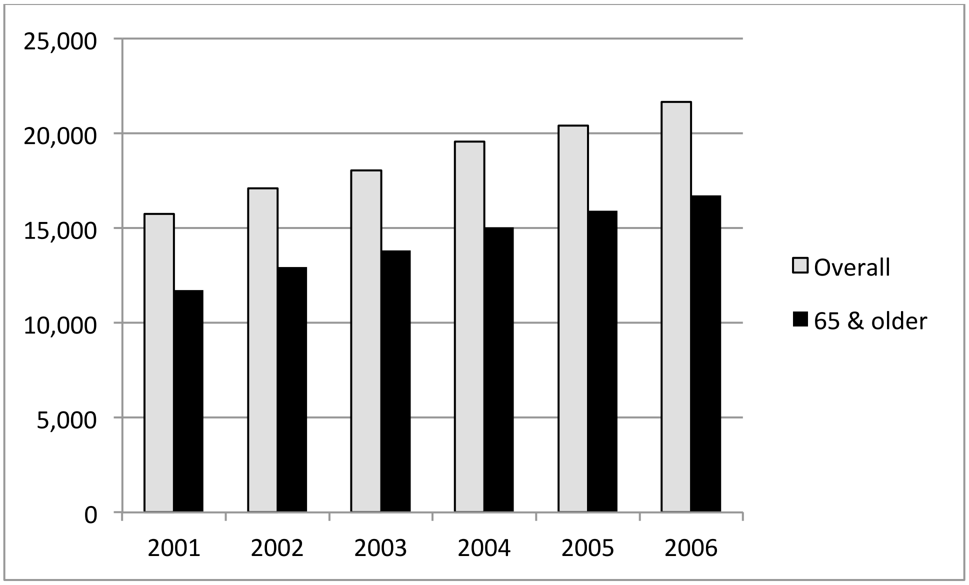
1.3. Summary

In summary, three specific research questions were addressed in this work. (1) What are the important determinants of gait factors that can affect slip and fall risk? (2) Can these DoG parameters used to assess slip and fall risk for different age groups, as well as between different walking conditions? (3) Is it possible to use inertial measurement units to measure DoG parameters and therefore assess slip and fall risk? Answers to these questions not only enhanced our knowledge about the effects of gait characteristics on slip and fall risk, but also provided a new solution of non-intrusive slip and fall risk assessment during daily living.

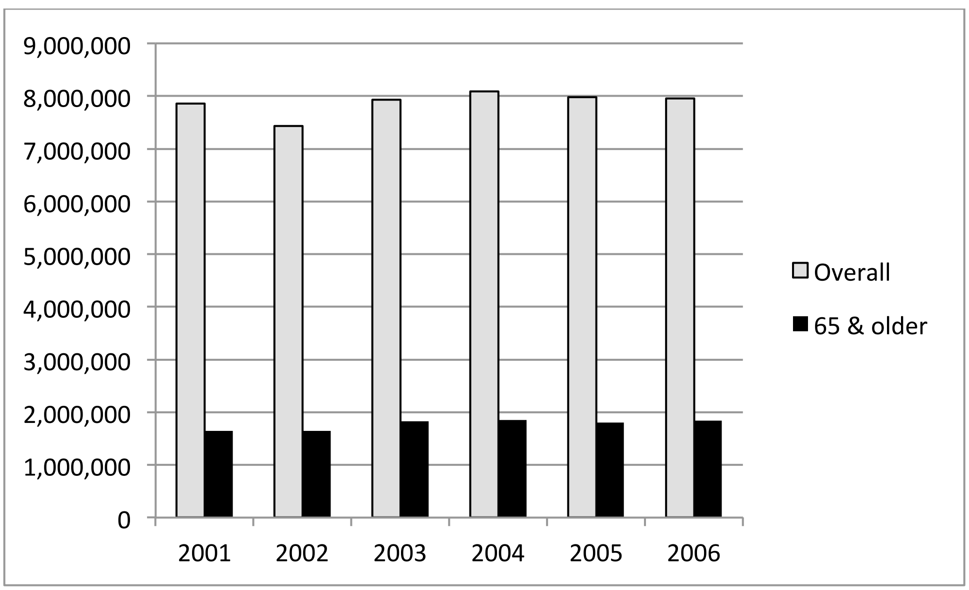
2. LITERATURE REVIEW

2.1. An Overview of the Fall Problem

Statistics from the Centers for Disease Control and Prevention show that fall accidents have become a serious health threat for the US population. In recent years, unintentional falls were the No. 1 leading cause of nonfatal accidental injuries and one of the top three causes of accidental deaths across all age groups. The number of fall related injuries and fatalities is even larger than the number of injuries and fatalities caused by motor vehicle traffic accidents (CDC, 2009b). More significantly, the magnitude of the fall problem is increasing. From the year 2001 to 2006, fall related fatalities multiplied about 1.4 fold (Figure 1). Among older adults, fall accidents can be even more severe because of the physical, sensory, and cognitive degradations among older adults (Lockhart et al., 2003; Lockhart et al., 2002). For example, in 2006, people 65 or older, which constituted 12% of the total population, accounted for 23% of the nonfatal fall injuries and 77% of the fall related injury deaths (CDC, 2006, 2009b).



(a) Number of fall related fatalities



(b) Number of fall related non-fatal injuries

Figure 1: Fall related fatalities and non-fatal injuries in the U.S. 2001-2006 (CDC, 2009b)

Because of the significance of the fall problem, researchers and clinicians have studied the fall problem for several decades. Their efforts have led to the development of multiple interventions. Based on the mechanism, these interventions can be categorized into two types: reactive interventions and proactive interventions (Marletta, 1991; Rubenstein, 2006).

Reactive interventions aim at minimizing fall related injuries. Traditionally, this objective was achieved by applying personal protective equipment (PPE) to reduce fractures, e.g. hip protectors and soft floors (Casalena et al., 1998; Kannus et al., 2000; Lauritzen et al., 1993; Simpson et al., 2004). With emerging information technology, real-time detection of a fall has become a promising area. Motion characteristics such as post-fall postures, impact forces and free falling kinematics have been used to detect the occurrence of a fall (Doughty et al., 2000; Noury et al., 2003; M N Nyan et al., 2006). This information can be sent to a remote monitoring center by wireless networks to summon immediate medical care (Lee & Mihailidis, 2005; Zhang et al., 2006), or used to trigger on-demand protective equipment such as a wearable airbag (Fukaya & Uchida, 2008). These active protection techniques, if applied, could be beneficial in alleviating the consequence of a fall.

Effective as they might be, reactive interventions are not designed to prevent falls from occurring. In that regard, proactive interventions are needed to reduce the potential of falls prior to the fall event. As such, understanding risk factors associated with a fall becomes essential in the development of proactive interventions. In general, fall risk factors can be categorized into extrinsic (environment) and intrinsic (individual) factors. Typical extrinsic factors include slippery or uneven floor surfaces, ill-designed stairways, poor lighting, etc. (Gill et al., 2000; Nevitt et al., 1991). Most of these hazards can be controlled using engineering measures. Major intrinsic factors include musculoskeletal degradations, sensory or cognitive impairments, inappropriate medications, etc. (Cesari et al., 2002; Stalenhoef et al., 1997). Certain intrinsic risk factors can be controlled by walking aids, gait and balance training, physical therapy and medical treatment (Cesari et al., 2002; Close, 2005).

In summary, both reactive and proactive interventions have been demonstrated to be helpful in reducing fall accidents. However, due to the constraints of funding, staffing and equipment, intervention-oriented fall risk assessment is needed to help screen out the most fall prone individuals and specify the most appropriate interventions.

2.2. Existing Fall Risk Assessments

Based on types of measurements, fall risk assessments can be roughly divided into clinical fall risk assessments and functional fall risk assessments (Perell et al., 2001).

2.2.1. Clinical fall risk assessments

Clinical fall risk assessments have been widely performed as screening tools upon admission or for regular examination in various clinical settings. They employ standard instruments or forms to collect health and medical information from the patient's self-report or by the judgment of the nursing staff (Perell et al., 2001). Based on the general relationship between fall risk and these health and medical status, an estimate of the patient's fall risk is derived. Clinical fall risk assessments are typically non-intrusive, fast, and easy to operate, thus preferred in medical facilities. However, these assessments highly depend on the observation and judgment of the nursing staff or the self-report from the patient. Therefore the objectivity and reliability of these methods can be problematic (Dowding & Thompson, 2003).

Morse (2006) suggested three general steps to develop clinical fall risk assessments systematically. The first step is an exploration of various possible risk factors primarily based on expert opinions and literature review. Next, risk factors should be screened by certain gold standards of fall risk. Those factors found to be highly correlated with the standards are kept and those less relevant are eliminated. Finally, selected factors should be assigned with levels or scores. Statistical weight for each factor can be further determined according to the statistical importance of the factor.

One of the first fall risk assessment methods that exactly followed the procedures as described above was Morse Fall Scale (MFS), which was developed for the purpose of evaluating a patient's likelihood of a fall both in the hospital and in inpatient long term care settings (J.M. Morse et al., 1989). MFS was initially developed using a database of one hundred fallers and one hundred non-fallers. A large number of variables were measured and their differences between fallers and non-fallers were analyzed. Six variables were eventually selected, which were history of falling, secondary diagnosis, ambulatory aid, IV/heparin lock, gait/transferring and mental status. The weight of each variable was computed and used to determine the score for the variable. Three risk levels and corresponding intervention protocols were specified based on the total score of all the six variables (J. M. Morse, 1997). The original authors reported the sensitivity and specificity in classifying the high-risk group as 78% and 83% respectively.

Despite the wide acceptance of MFS, subsequent studies found generalization problems when the scale was applied in inpatient hospital settings (O'Connell & Myers, 2002). Further, the cut-off scores that differentiate high risk and low risk groups are still under discussion (Schwendimann et al., 2006). However, as a preliminary screening tool that requires less than a minute, MFS has achieved remarkable success. It is currently the fall risk assessment tool used by the United States Department of Veterans Affairs (2010). The systematic procedures used to develop MFS continue to serve as a valuable reference for fall risk assessment studies.

Concurrent with MFS development, Hendrich (1988) developed a fall risk assessment model for acute care patients. The model was revised several times later (A. L. Hendrich et al., 2003; A. Hendrich et al., 1995) and the current version is Hendrich II, a scale with eight clinical risk factors (i.e. confusion/disorientation, depression, answers to the Bender Elimination Test (BET), dizziness/vertigo, gender, antiepileptics, benzodiazepines and performance of rising from chair). These eight risk factors were initially selected from more than six hundred factors using stepwise logistic regression. A different weight was assigned to each of them. A total score greater than 5 (out of 16) indicated high risk. The model was validated retrospectively by three hundred and fifty-five fall prone patients and seven hundred and eighty controls in a population drawn from a seven-hundred-and-fifty-bed acute care hospital over a two-year period. The reported sensitivity and specificity was 74.9% and 73.9% respectively. The most significant contribution of Hendrich II, from a methodological perspective, is the extensive screening of over six hundred risk factors and the involvement of mental health factors. However, the validity of this model appears to be limited to acute care settings. Later studies have reported unsatisfactory accuracy when using this model in other settings such as nursing homes (Heinze et al., 2009) and surgical sectors in hospitals (Lovallo et al., 2010).

Another fall risk assessment method requiring nursing judgment is the <u>St Thomas Risk Assessment Tool in Falling Elderly Inpatients (STRATIFY)</u> (Oliver et al., 1997). It is comprised of five factors regarding the patient's history of falling and other clinical characteristics. The five factors were initially selected from twenty-one factors according to their odds ratios of fall. Each factor was scored 1 or 0, and the total score, ranging from 0 to 5 was used to identify the fall risk. A cut-off value of 2 or 3 was recommended. Although the original method did not consider the weight for each of the factors, a later revision of the STRATIFY employed multivariate logistic regression to obtain optimal weight for each factor and a receiver-operating characteristic (ROC) curve to search the best cut-off value (Papaioannou et al., 2004). With a final design of a 30-point scale, a sensitivity of 91% and specificity of 60% for predicting who would fall was reported based on a sample of over one thousand patients. Unfortunately, when used among other samples, the test accuracy was inconsistent. For example, Vassallo et al. (2008) reported that the use of STRATIFY was no better than the simple clinical observation of wandering behaviors, thus challenging the usefulness of STRATIFY.

One common shortcoming of the above three fall risk assessment tools is that there is generally no way to separate the effect of each risk factor on falls. Therefore, the determination of the weight of each factor was solely based on statistical analysis. The benefit of assigning such weight, therefore, remains unclear. For example, Heinze et al. (2006) found a high correlation between weighted scores and unweighted scores obtained from Hendrich II model and thus recommended the unweighted method for simplification. Similarly, there are a number of fall risk assessment methods that do not have weighted risk factors but that have been widely used in practice.

The <u>Downton Fall Risk Index (DFRI)</u> is such an example (Downton, 1993). It evaluates the fall risk from five categories: known previous falls, medications, sensory deficits, mental states and gait. Options are given under each category to be chosen, and a selection of greater than 3 options (out of 11) was considered an indicator of high risk of fall (Nyberg & Gustafson, 1996). DFRI has been validated by a group of one hundred and thirty-five patients admitted to a geriatric stroke rehabilitation unit. The sensitivity of the fall prediction was 91%, whereas the specificity was as low as 27%.

Several other clinical fall risk assessment methods used very similar development methodology and implementation procedures. For example, MacAvoy et al. (1996) developed a Fall Risk Assessment Tool (FRAT) consisting of eight categories: age, mental status (confusion and agitation), elimination, history of falls, sensory impairment, activity and medications. The sensitivity of FRAT was reported as 70% but the specificity was only 43%. Cwikel et al. (1998) designed an Elderly Fall Screening Test (EFST) consisting of questions on the history of falling and evaluations of gait patterns. The reported sensitivity was 93% and specificity was 78%. Mertens et al. (2007) tested a twelve-item Nursing Care Dependency Scale (NCD) developed by Dijkstra et al. (1999) and found that using "avoidance of danger" as an exclusive distinction criterion for high fall risk resulted in high sensitivity (96%) and low specificity (13%) in nursing homes, and high sensitivity (79%) and moderate specificity (68%) in hospitals. Robey-Williams et al. (2007) proposed the Spartanburg Fall Risk Assessment Tool (SFRAT), a three-step procedure with five true-or-false questions to assess fall risk for the acute care population. The predictability analysis found perfect sensitivity (100%) of SFRAT but poor specificity (28%).

A few other clinical fall risk assessment methods have been applied within certain individual institutes without sufficient validation. Examples of these assessments include the High Risk for Falls Assessment Form (Young et al., 1989), Royal Melbourne Hospital Risk Assessment Tool (Mercer, 1997), Reassessment Is Safe Kare (Brians et al., 1991), Fife Scale (Fife et al., 1984), and Johns Hopkins Fall Risk Assessment Tool (Poe et al., 2005).

While most of the clinical fall risk assessment methods primarily address the clinical history and physical performance of the patients, other assessments evaluate the psychological aspects of the fall risk. One of the most common psychological risk factors is the fear of falling. For example, the <u>Fall Efficacy Scale (FES)</u> initially designed by Tinetti et al. (1990) measures the confidence in performing a range of daily activities without falling. The first version of FES included ten activities of daily living with a scale from 1 to 10 assigned to each activity. Later the authors changed FES to 4-level scales. The revised FES was found to be sensitive to fear levels after clinical interventions (Tinetti et al., 1994). Other researchers further developed this scale into a sixteen-item questionnaire, the <u>Fall Efficacy Scale International (FES-I)</u> (Yardley et al., 2005). FES-I was found sensitive to group differences on demographic characteristics and fall risk factors. A total score greater than 23 (out of 64) for FES-I was considered an indicator of a "high concern about falling" (Delbaere et al., 2010).

Another study derived from the original FES resulted in the <u>Activity-specific Balance Confidence (ABC) Scale</u> (Powell & Myers, 1995). It was based on the same operational definition of fear of falling as a "low perceived self-efficacy at avoiding falls during essential, nonhazardous activities of daily living" (Tinetti et al., 1990) but included a wider continuum of activity difficulty and more detailed item descriptions (Powell & Myers, 1995). The authors suggested that the sixteen-item ABC scale was more suitable for moderate to high functioning older adults compared with FES (A. M. Myers et al., 1998). A series of studies demonstrated that ABC scale can discriminate between higher and lower functioning older adults and was sensitive to the effects of training, physical therapy and hip or knee surgeries (Beninato et al., 2009; Lajoie & Gallagher, 2004).

Table 1 summarizes clinical fall risk assessment methods that have been widely used.

Table 1: Clinical fall risk assessment methods

Name	Authors	No. of Risk Factors	Sensitivity & Specificity
MFS	Morse et al., 1989	6	78% and 83%
Hendrich II	Hendrich, 1988	8	75% and 74%
STRATIFY	Oliver et al., 1997	5	91% and 60%
DFRI	Downton, 1993	5	91% and 27%
FRAT	MacAvoy et al., 1996	8	70% and 43%
EFST	Cwikel et al., 1998	2 categories	93% and 78%
NCD	Dijkstra et al., 1999	12	96% and 13% in nursing homes 79% and 68% in hospitals
SFRAT	Robey-Williams et al., 2007	5	100% and 28%
FES	Tinetti et al., 1990, 1994	10	N/A
FES-I	Yardley et al., 2005	16	N/A
ABC	Powell & Myers, 1995	16	N/A

2.2.2. Functional fall risk assessments

Functional performance tests are another widely used method to assess the fall risk. The major principle behind this method can be explained in the following way: a fall is a special case of unsuccessful balance control. Although it might be difficult to directly measure one's capability of balance maintenance during a fall, this capability can be reflected in the performance of other daily activities which utilize similar mechanisms of balance control, such as standing, normal walking, bending and reaching. Typically, functional fall risk assessments focus on capabilities and limitations of posture and gait, and assess various motion characteristics in an objective or mostly objective way (Perell et al., 2001).

A number of studies selected individual functional performance parameters to indicate fall risk. Examples of these parameters are: 1) basic gait characteristics such as step length (J. M. VanSwearingen et al., 1998), walking speed (Sieri & Beretta, 2004), and forward and backward tandem walk capability (Dargent-Molina et al., 2002; Palombaro et al., 2009); 2) posture transition performance such as stand-to-sit and sit-to-stand transition (Alexander et al., 1991; Najafi et al., 2002b); 3) balance and stability characteristics such as posture sway (Stalenhoef et al., 2002), dynamic balance (Rogers et al., 2003), gait dynamics (J. Hausdorff et al., 2000; J. M. Hausdorff, 2007; J. M. Hausdorff et al., 2001), and limits of stability (Sze et al., 2008); 4) lower extremity muscle and joint capabilities such as knee and ankle joint torque and power (S. R. Lord et al., 2005) and lower limb muscle strength (S. R. Lord et al., 2005); 5) upper extremity functions such as functional reach (Duncan et al., 1990; Thapa et al., 1996); and 6) neuron-muscular performance such as reaction condition in a quick stepping test (Luchies et al., 2002) and probe reaction time during walking (Huo et al., 2009). In general, most of these studies succeeded in demonstrating significant group difference in these parameters, but the theoretical relationship between these parameters and the actual fall risk has not been sufficiently justified.

Another way to assess functional performance is through standard functional tests. The most prevalent one among these tests is probably the <u>Timed Get-up and Go (GUG) Test</u> (Mathias et al., 1986). From the early development in 1986, this simple test has been used by numerous studies and has demonstrated its usefulness for assessing basic functional mobility. As suggested by the name, GUG test is made up of a series of basic motions including standing up from a chair, walking forward for three meters, turning around, walking back and sitting down. The original GUG test used observational ratings on the performance, but it was later modified to use an objective measurement of the overall movement time (MT) consumed to complete the whole task as the fall risk indicator. Specifically, MT greater than 20 seconds was considered abnormal (Podsiadlo & Richardson, 1991).

GUG test has been used extensively and increasingly throughout the years, while the criticism of it continues as well (Lindsay et al., 2004; Wall et al., 2000). Based on the original design, a few modified versions of GUG test have been developed with additional measurements during the test. For example, the <u>Expanded Timed Get-up and Go (ETGUG) Test</u> increases the walking distance to ten meters and breaks down the task into six phases: sitting to standing, gait initiation, walking 1, turning around, walking 2 and sitting down (Wall et al., 2000). Each phase time is recorded and used for group comparison. As suggested by the authors, the ETGUG isolated functional deficits better than the original GUG, which could be helpful for recommending specific interventions.

During the same year of the development of GUG test, Tinetti (1986) proposed the <u>Performance Oriented Mobility Assessment (POMA)</u>, a functional test measuring older adults' gait and balance capabilities. POMA uses the same equipment as GUG test (i.e. a chair, a stopwatch and a walkway) but examines functional performance particularly focusing on lower extremities. In the balance test part, nine postures or movements requiring balance control skills are tested. The grading of each item is based on observation, and the overall balance scores range from 0 to 16. In the gait test part, seven gait characteristics are evaluated and the final gait scores range from 0 to 12. A total score (balance and gait) less than 19 is considered as high fall risk, 19-24 for medium fall risk and 25-28 for low fall risk. Generally, POMA is more time consuming than GUG, but the multiple assessments for balance and gait could help clinicians evaluate the patient's mobility problem in greater detail.

The <u>Guralnik Test Battery (GTB)</u> also focuses on the functional performance of the lower extremities (Guralnik et al., 1994). In addition to assessing the balance and gait factors assessed in POMA, GTB adds measurements of strength and endurance. Tasks of GTB involve standing with the feet together in the side-by-side, semi-tandem, and tandem positions, walking for 8 feet, and rising from a chair and returning to the seated position for five times. Both subjective rating and objective measurements (i.e. time) are used.

Another functional test with multidimensional assessments is the Berg Balance Test (Berg, 1989), which has fourteen basic daily activities with a 0 to 4 grading scale associated with each activity. Originally Berg determined a cut-off score of 45 (out of 56) to differentiate fallers and non-fallers. To increase the specificity, Riddle and Stratford further suggested a lower cut-off score of 40 (Riddle & Stratford, 1999). Compared with POMA and GTB, the Berg test further examines functional performance of upper extremities such as maximal reaching, and involves some higher functioning activities such as standing with one foot. Consequently, the Berg test appears more feasible for those with general physical health, but not those who are extremely frail.

Beyond the normal walking tasks, the Dynamic Gait Index (DGI) involves eight walking conditions of increased difficulty. The eight walking conditions are: walking on a level surface, with changing speed, with horizontal head turns, with vertical head turns, with pivot turns, over an obstacle, around and obstacle, and up stairs (Shumway-Cook & Wollacott, 1995). These tasks are graded on a 4-level scale from normal performance (3) to severely impaired (0). A total score of 19 or less is considered an increased risk of falls among the elderly. The use of more difficult functional tasks in DGI could be beneficial because too simple tasks are likely to induce ceiling effects. However, increasing task difficulty could also induce additional risk during the test and limit the application of such a test.

The multi-activity functional assessments discussed above mainly use descriptive criteria of performance (e.g. able to…, not able to…, requiring hand support…, etc.). The Physical Performance Test (PPT), on the contrary, assesses each item solely by the time required to perform the task (Reuben & Siu, 1990). PTT has both a nine-item version and a seven-item version, with each item assigned a 0-4 scale. Cut-off time for each activity was originally determined by examining the distribution of the scores obtained from five different patient populations. The highest level of each scale roughly represents subjects in the top 20%.

Beyond simple observation and time recording, motion capture techniques such as videotaping have also been used in the design or implementation of functional tests. The Gait Abnormality Rating Scale (GARS) is such an example (Wolfson et al., 1990). In the original study, GARS measurements consisted of stride length, walking speed and a videotape-based analysis of sixteen facets of gait. Arm swing amplitude, upper-lower extremity synchrony, and guardedness of gait were determined to be most impaired in fallers. Consequently, a Modified GARS (GARS-M) was developed using seven assessment items: variability, guardedness, staggering, foot contact, hip ROM, shoulder extension, and arm-heel-strike synchrony, each with a 0-3 rating scale (Jessie M VanSwearingen et al., 1996). In general, evaluations in GARS-M are more time-consuming than evaluations in the functional tests previously discussed. For example, in POMA, one could rate the performance of sitting down as “safe”, “safe if with arm support” and “unsafe” merely by one-time observation; while in GARS-M, it is necessary to use repeated playback, slow action and stop action to catch the foot contact moments and determine the score (Jessie M VanSwearingen et al., 1996). Furthermore, because of the complexity of the measurements, reliability of the assessment could be an issue. In that regard, Van Swearingen et al. (1996) investigated the intra-rater and inter-rater reliability of GARS-M and found moderate agreement for the scoring for six GARS-M items but lack of agreement on the staggering measurement.

The Physiological Profile Assessment (PPA) addresses the physiological profile of daily functions as well as kinematic and kinetic profiles. PPA involves a series of simple tests of vision, peripheral sensation, muscle force, reaction time, and postural sway, which are believed to be primary contributors to stability (Stephen R Lord et al., 2003). Measurements within each test were originally selected according to seven criteria: simple, short, feasible for the elderly, valid and reliable, low-tech and robust, portable, and quantitative. Unfortunately, the grading scheme of PPA has not been disclosed in detail. Instead, the authors developed an online program to assess an individual's performance in relation to a normative database compiled from large-scale studies. Four categories of assessments were provided by the program: a graph of the overall fall risk score, a profile of the test performances, a table indicating test performances in relation to age-matched norms, and a written report that explains the results and makes recommendations for improving functional performance.

Functional fall risk assessments, in general, demonstrate the methodology to assess fall risk objectively without actually making the subject fall. However, in practice the problem is still unsolved. The key issue is the design and justification of the functional parameters measured. Traditionally, this has been done mainly by intuitive selection, and the details of the functional task such as how long to hold a position or how far to walk were determined even more arbitrarily. Without thorough understanding of the theoretical relationships between these parameters and the fall risk, the functional assessments could be weak in theory and therefore less reliable. Furthermore, the outputs of most functional risk assessments are simple risk scores indicating the overall fall risk. These scores, even if well validated, are insufficient to diagnose the specific factors causing fall risk. Therefore, a new method of fall risk assessment incorporating theoretical foundations is needed to identify individuals with high fall risk and specify the causes of their fall risk.

Table 2 summarizes typical functional tests used for fall risk assessment.

Table 2: Functional fall risk assessment methods

Name	Authors	Measurements in the test	Criterion for high fall risk
GUG	Mathias et al., 1986	Movement time (MT)	MT > 20 seconds
ETGUG	Wall, et al., 2000	Separate phase times	N/A
POMA	Tinetti, 1986	Balance: 9 postures / motions Gait: 7 characteristics	Total score < 19 (out of 28)
GTB	Guralnik et al., 1994	Balance, gait, strength and endurance	N/A
Berg	Berg, 1989	Grading of 14 basic daily activities	Total score < 40 or 45 (out of 56)
DGI	Shumway-Cook & Wollacott, 1995	Gait performance under 8 walking conditions	Total score < 19 (out of 24)
PPT	Reuben & Siu, 1990	Time required to perform 9 or 7 tasks respectively	N/A
GARS	Wolfson et al., 1990	Stride length, walking speed and a videotape-based analysis of gait	N/A
GARS-M	VanSwearingen et al., 1996	Performance of 7 functional tests	N/A
PPA	Stephen R Lord et al., 2003	Vision, peripheral sensation, muscle force, reaction time, and postural sway	N/A

2.3. Gait and Fall Mechanisms

2.3.1. Definitions of gait and fall

From the kinesiology perspective, human gait is a continuous process of transferring one's body weight from one place to another (Marletta, 1991). A gait cycle starts from the initial heel contact of the contacting foot and ends at the next consecutive heel contact of the same foot. Two main phases are involved in this cycle: the stance phase (when the foot is in contact with the ground, approximately from 0% of the gait cycle to 60% into the gait cycle) and the swing phase (when the foot is not in contact with the ground, approximately from 60% of the gait cycle to 100% of the gait cycle) (Vaughan et al., 1999). Both of them can be further divided into several sub-phases. For example, Cochran (1982) divided the stance phase into initial contact (0%), loading response (0-10%), midstance (10-30%), terminal stance (30-50%) and preswing (50-60%), and the swing phase into initial swing (60-70%), midswing (70-85%) and terminal swing (85-100%). Figure 2 demonstrates a typical gait cycle.

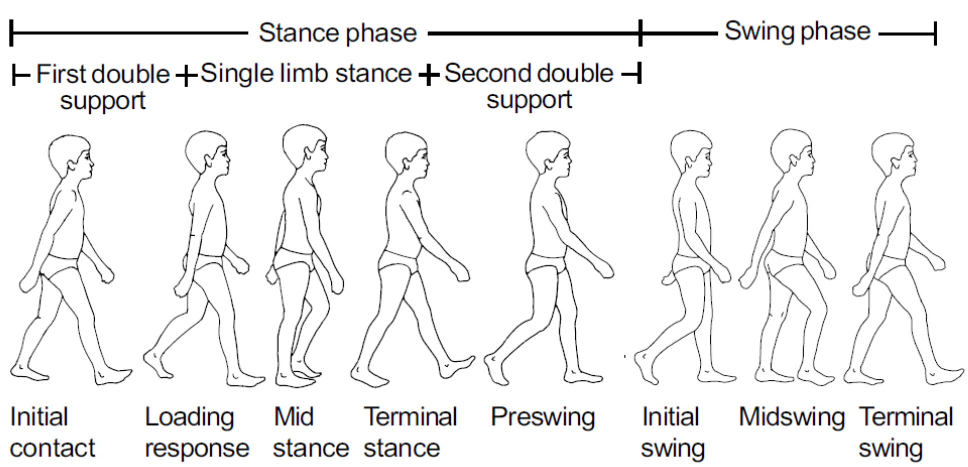


Figure 2: A typical gait cycle

Figure adopted from Vaughan et al. (1999)

From a biomechanical perspective, the cyclic gait can be seen as a repeated process of losing and regaining balance. Even during steady-state walking the whole body CoM is almost always outside the base of support, except for the short period during the double support phase (Winter, 1995b). However, because of the cooperation between the sensory system, center nervous system, and musculoskeletal system, the displacement of the whole body CoM with reference to the base of support is controlled within a range during normal gait cycles, such that the temporary loss of local balance could be immediately modulated during the next stance phase. Consequently, delayed or insufficient transition of the whole body CoM may result in a global loss of balance, break out the chain of body weight transferring, and even cause a fall (Lockhart et al., 2003).

A fall, as defined by the Kellogg International Work Group, is "unintentionally coming to ground, or some lower level not as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure" (Gibson, 1987). Two important features of a fall are indicated in this definition. First, a fall involves a change of position from standing or sitting to reclining or lying. Second, a fall is an unintentional movement, which makes it distinct from intentional activities such as lowering the whole body in sides.

A fall can be divided into three phases: initiation, detection and recovery (Lockhart, 2008). A fall is typically initiated with a significant perturbation on balance such as a slip or a trip (Courtney et al., 2001). According to the direction of the perturbation, a fall could initiate in the forward, backward or lateral direction (Noury et al., 2007). Immediately following fall initiation, a free falling period starts. One or more sensory systems (proprioception, vision, and vestibular function) detect the loss of balance, alert the center nervous system (CNS) to a potential fall, and trigger musculoskeletal responses (i.e. reactive recovery) (Lockhart, 2008). Non-optimal detection and recovery, as often indicated by excessive trunk angular velocity, makes the body finally hit the ground or an obstacle (M. N. Nyan, F. E. H. Tay, A. W. Y. Tan, et al., 2006). The impact shock further results in an intense inversion of the polarity of the acceleration vector, which may cause significant consequences such as hip fractures, head injuries and other traumas (Noury et al., 2007).

2.3.2. Slip induced backward falls

As mentioned earlier, this study focuses on slip induced backward falls. Literature suggests that local heel sliding occurs in every gait cycle immediately after heel contact (Redfern et al., 2001). As such, a sufficient acceleration in the opposite direction to the heel sliding velocity is required to terminate initial heel sliding motion. During normal walking, it is the frictional force between the sole and the floor surface that provides the acceleration, stabilizes the foot and then pushes the body forward (Strandberg & Lanshammar, 1981). Furthermore, tribology suggests that the frictional capability of a shoe-floor interface is fixed. While the foot is moving, frictional capability of an interface can be represented by the dynamic coefficient of friction ($dCOF$) (Perkins & Wilson, 1983). If the actual friction demand (as quantified by the required coefficient of friction; $rCOF = \frac{vertical\ GRF}{horizontal\ GRF}$) is greater than the $dCOF$ of a certain shoe-floor interface, a slip is likely to initiate (Redfern et al., 2001).

The severity of slip initiation can be represented by kinematics in the slip initiation phase (SPI) defined by Lockhart et al. (2003). Specifically, SPI starts at the moment when the non-rearward positive acceleration of the foot after heel contact occurs, and ends at the moment when the sliding heel acceleration reaches its maximum. The heel contact velocity (HCV) and the slip distance during SPI (SDI) are important measures of slip initiation severity and can be used to differentiate negligible heel sliding (NS) and significant slips (SR and SF). For instance, a slip distance greater than 1 cm can be considered as a significant slip (Perkins, 1978; Redfern et al., 2001).

After a slip is initiated, performance of CoM transition determines the severity of slip development. Since most slip induced falls are backward, the capability to rapidly bring the CoM forward appears critical (Lockhart et al., 2003). In general, if a slip develops to a certain magnitude due to delayed or insufficient CoM transition, a fall is unlikely to be avoided regardless of how hard the individual acts thereafter (Redfern et al., 2001). In that light, kinematics in the slip development phase (SPII) defined by Lockhart et al. (2003) can be used to represent slip development severity. Specifically, SPII starts at the stop moment of SPI and ends when the first maximum of the horizontal sliding heel velocity occurs. The peak sliding heel velocity (PSHV) and the slip distance during SPII (SDII) are important measures of slip development severity. For instance, Redfern et al. suggested that a slip with an overall slip distance longer than 10 cm was unlikely to recover (Redfern et al., 2001).

In summary, the combination of HCV, SDI, PSHV and SDII is likely to be a good set of measurements depicting a heel sliding motion, or, the severity of a slip. Any extrinsic or intrinsic perturbation, which influences the friction demand and the CoM transition performance, eventually results in changes in these slip severity measures.

2.3.3. Determinants of gait

Various gait models exist, among which the "determinants of gait" model appears to be a very useful method for investigating normal and pathological gait (McMahon, 1984; Saunders et al., 1953). The determinants of gait model, which originated in a paper of Saunders et al. in 1953, describes six important lower extremity motions during a gait cycle. The combination of these determinants of gait well defines the complex movements during walking. The six determinants of gait (DoGs) are: 1) pelvic rotation, 2) pelvic tilt, 3) knee flexion of the stance leg, 4) ankle flexion about the heel, 5) foot rotation about the fore part of the foot, and 6) lateral displacement of the pelvis. Each of the DoGs allows for the introduction of one more degree of freedom (Batterman & Batterman, 2005). The net effect of all DoGs flattens the arched whole body CoM pathway during walking and reduces the jerky motions at intersections of consecutive arcs (McMahon, 1984; Saunders et al., 1953).

The compass gait (Figure 3) is a simplification of human gait, which neglects ankle, knee and pelvis motions. In the compass gait mode, the only motions of the lower extremities are hip flexion and extension (Inman et al., 1981). From a temporal perspective, the compass gait determines the cyclic feature of walking. From a spatial perspective, the compass gait can be considered as a series of pendulum (or inverted pendulum) motions that define the arched shape of the whole body CoM pathway.

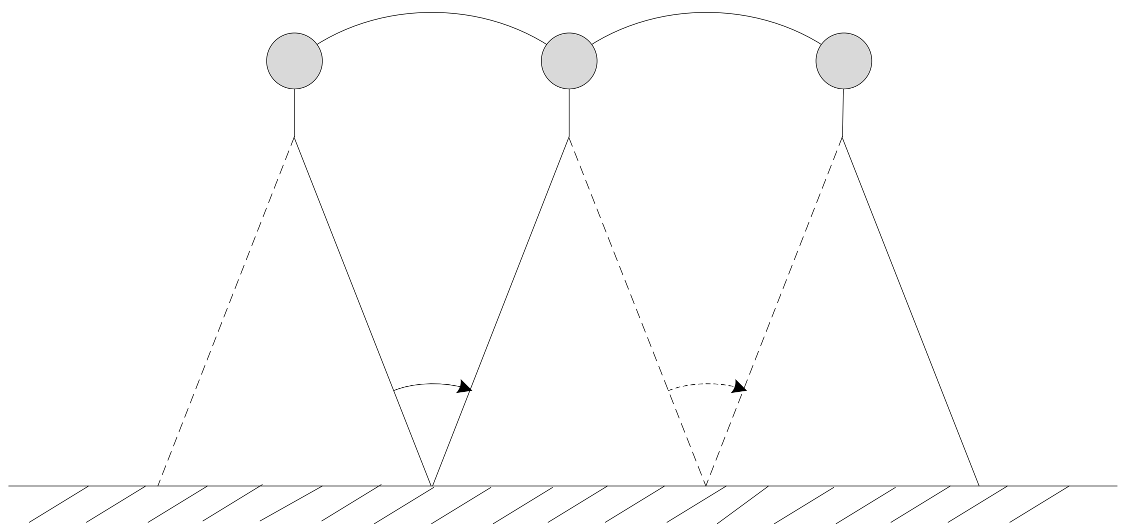


Figure 3: An illustration of compass gait

However, lower extremities are not rigid bodies. Motions other than hip flexion and extension modify the gait. The pelvic rotation refers to the rotation of the pelvis about a vertical axis. During walking, pelvic rotation occurs in the clockwise and counterclockwise directions alternately and reaches its maximum approximately at heel contact (Inman et al., 1981). Because of the pelvic rotation, the equivalent radius of CoM vertical arcs is lengthened and the extremities of the arcs are elevated towards the summits. Consequently, the vertical displacement of the CoM is reduced and intersections of CoM arcs are smoothed.

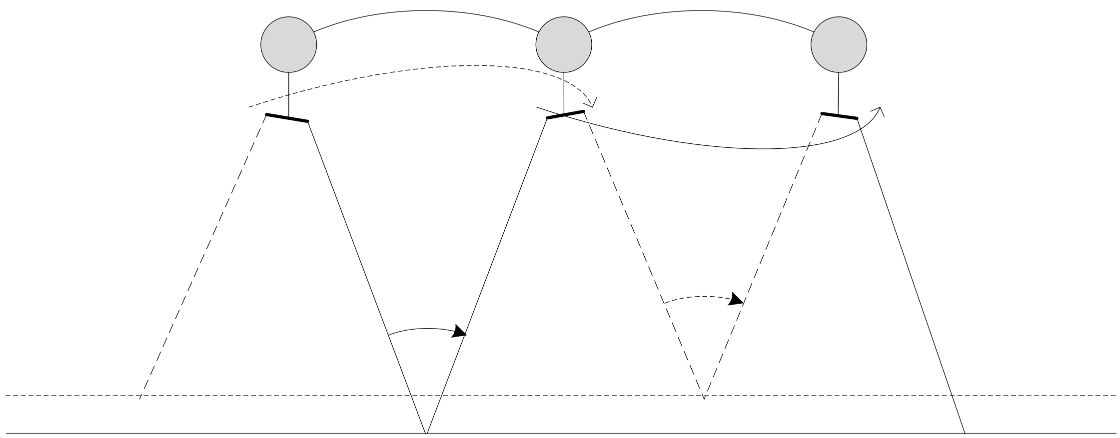


Figure 4: An illustration of pelvic rotation

The pelvic tilt (Figure 5) refers to the motion that the pelvis lists downward relative to the transverse plane on the side opposite to that of the weight-bearing limb (i.e. the hip on the swing side falls lower than the hip on the stance side) (McMahon, 1984; Saunders et al., 1953). Pelvic tilt helps to flatten the CoM vertical arcs as well. However, unlike pelvic rotation that elevates the extremities of CoM arcs towards their summits, pelvic tilt reduces the CoM vertical displacement by lowering the summits of CoM arcs. Typically, pelvic rotation and pelvic tilt are out of phase. The lowering of the swing hip occurs abruptly at the end of the double support phase just before toe-off, and then the swing hip rises slowly during the swing phase (McMahon, 1984).

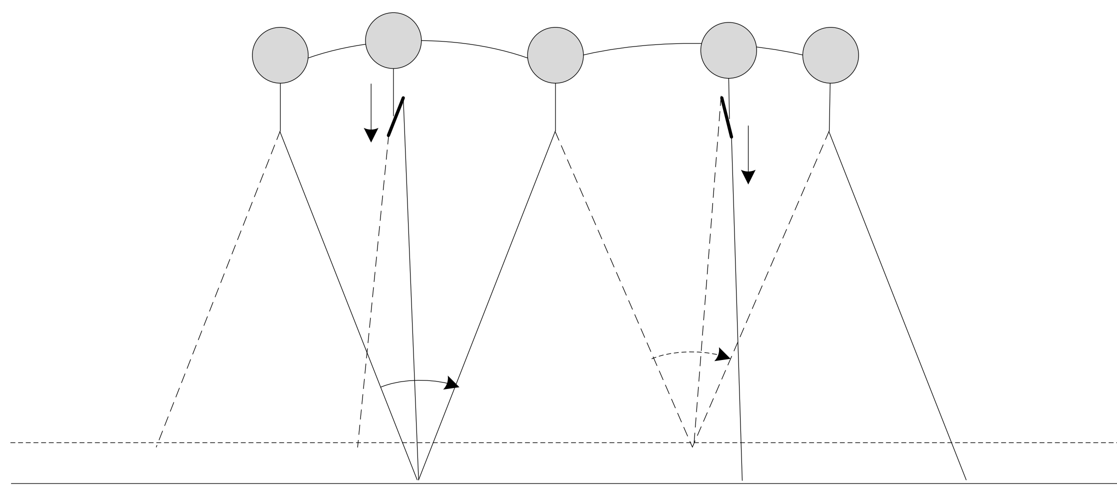


Figure 5: An illustration of pelvic tilt

When walking on a level surface, the knee of the stance leg bends immediately following heel contact. Such a motion is referred to as knee flexion of the stance leg (Figure 6) (McMahon, 1984; Saunders et al., 1953). Typically, the supporting limb enters the stance phase at heel contact with the knee joint at its maximal extension. Thereafter, knee flexion of the stance leg starts and the maximum knee flexion angle occurs immediately anterior to full weight-bearing (Inman, 1966). Similar to pelvic tilt, knee flexion of the stance leg lowers the summits of CoM arcs, thus reducing the CoM vertical displacement during normal walking. It also moderates the jerky motion following heel contact, thus smoothing CoM arcs at intersection points.

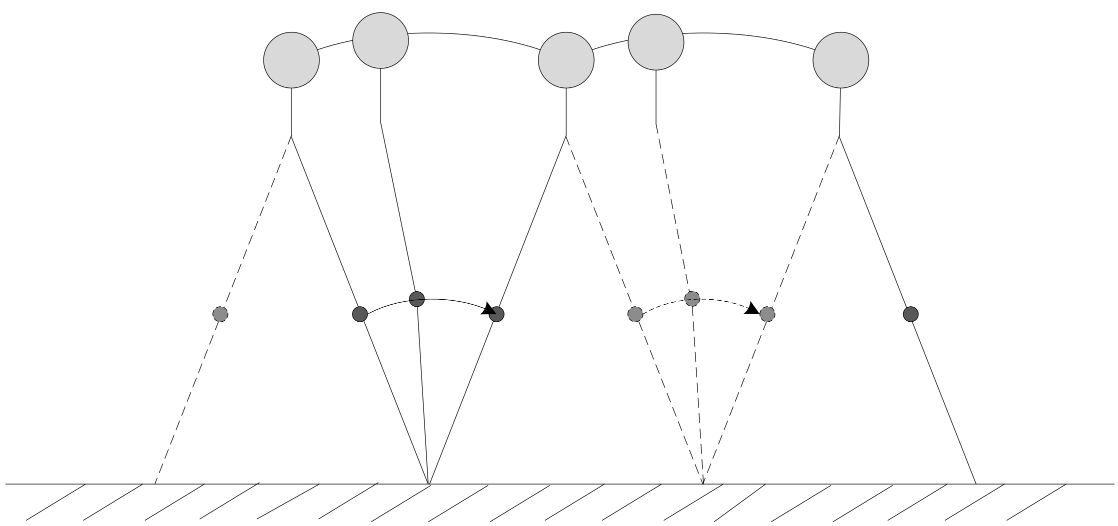


Figure 6: An illustration of knee flexion of the stance leg

Rotations of the stance foot (Figure 7) following heel contact further smooth the CoM pathway and reduce jerky motions. Rotations of the stance foot start with the ankle flexion about the heel (rotation I; RI), followed by the foot rotation about a center established at the fore part of the foot (rotation II; RII). The ankle angle reaches it maximum approximately at toe-off. Rotations of the stance foot also play an important role in establishing the initial velocities of the shank and thigh for the subsequent swinging motion (McMahon, 1984).

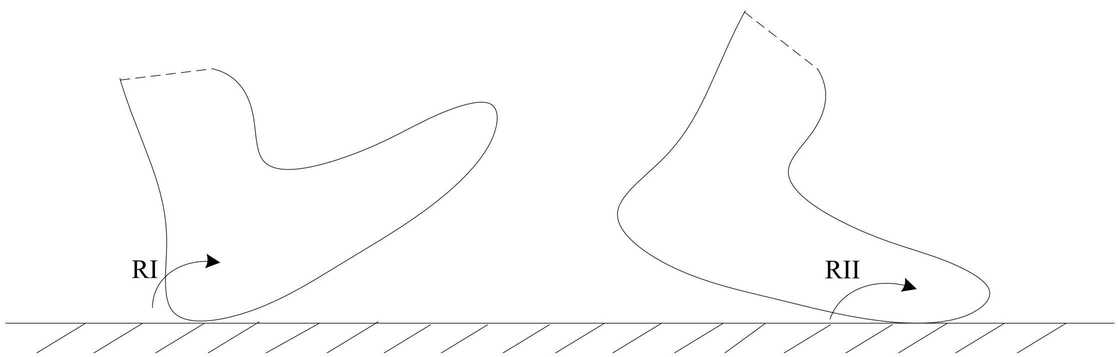


Figure 7: An illustration of rotations of the stance foot

The whole body CoM is not only displaced vertically, but also laterally while the weight bearing is alternately transferred from one limb to the other. Lateral displacement of the pelvis helps to correct the otherwise excessive lateral displacement of the CoM (Figure 8) (Saunders et al., 1953). Pelvis lateral displacement is produced by the horizontal shift of the pelvis and relative adduction at the hip. During normal walking, lateral displacement of the pelvis is coupled with pelvic rotation and pelvic tilt. However, it represents another degree of freedom of the pelvis.

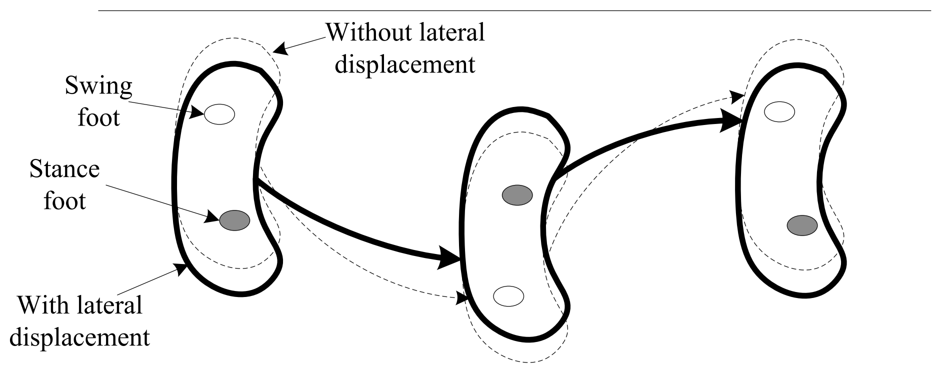


Figure 8: An illustration of lateral displacement of the pelvis

In summary, compass gait defines basic cyclic features of gait and formalizes the arched whole body CoM pathway during walking. Pelvic rotation, pelvic tilt, knee flexion of the stance leg, ankle flexion about the heel, and foot rotation about the fore part of the foot modify the CoM pathway in the plane of progression by flattening CoM arcs and smoothing intersections of consecutive arcs. Lateral displacement of the pelvis reduces the CoM lateral displacement. The original motivation of investigating the six determinants of gait was based on the assumption that reduced CoM displacement helped to conserve energy during walking (Saunders et al., 1953). However, later studies suggest that CoM displacement is not the only factor that determines energy requirement (Croce et al., 2001; Kerrigan et al., 2000). The intentional reduction of CoM vertical displacement during walking may even cost more energy (Ortega & Farley, 2005). As such, it appears more appropriate to consider the determinants of gait model as a kinematic model that describes important components of gait, rather than a kinetic model used to provide accurate prediction of energy consumption during walking.

2.4. Inertial Measurement Units Used in Motion Study

2.4.1. Inertial measurement units (IMUs)

An inertial measurement unit, or IMU, is a piece of miniature electromechanical device that measures linear accelerations, angular velocities and orientations (Benbasat & Paradiso, 2002). An IMU is typically composed of accelerometers, gyroscopes and sometimes magnetometers. Early applications of IMUs focused on guidance and navigation (Barbour & Schmidt, 2001). However, since the 1990s, inertial sensing techniques have been frequently used by human motion studies to estimate energy expenditure, monitor daily activities and characterize gait (K Aminian & Najafi, 2004).

An accelerometer is an instrument that measures the applied acceleration (i.e. the acceleration relative to an inertial frame) acting along a sensitive axis (Merryn J Mathie et al., 2004). Although mechanisms to measure acceleration are different based on the type of transducers (i.e. capacitive, piezoelectric, piezoresistive, hall-effect, magnetoresistive and heat-transfer), all of them use the variation of a spring mass system for sensing the applied acceleration (Merryn J Mathie et al., 2004; SENSR).

Accelerometers can be categorized based on their capability of measuring the gravity, or more accurately, the gravitational acceleration projected on the sensitive axis of the accelerometer (K Aminian & Najafi, 2004). Among common types of accelerometers, resistive and capacitive accelerometers are sensitive to both gravitational (static) and inertial (dynamic) components of acceleration, while piezoelectric accelerometers measure only the dynamic acceleration. In human motion studies, neither type is absolutely superior to the other. On one hand, the measurement of gravity can be useful because it provides information about the inclination of body segments (Hansson et al., 2001; Luinge & Veltink, 2004). On the other hand, the superimposing of the gravitational and inertial accelerations may require additional measurement or computation to separate these two components when the inertial acceleration is of interest (K Aminian & Najafi, 2004). Therefore, the selection of the appropriate type of sensors should be determined case-specifically.

Accelerometry has proven to be a very promising method for motion studies. In general, acceleration signals have been widely used for pattern recognition, event detection, time-frequency analysis, and biomechanical modeling (Wiebren Zijlstra & Hof, 2003). Major hardware issues associated with current accelerometers include the tradeoff between bandwidth and noise, zero g offset (i.e. voltage output at 0 g), A/D sensitivity, bias drift, and sensitivity drifting with temperature (Doscher, 2008).

A gyroscope is an instrument that measures the angular velocity about a sensitive axis (K Aminian & Najafi, 2004). According to the Coriolis effect, a rotating reference frame results in an apparent force (i.e. the Coriolis force), which is proportional to the angular rate of the rotation. Electromechanical gyroscopes typically use a vibrating mechanical element to transfer the energy generated by the Coriolis force, and then assess the vibration by piezoelectric, resistive or capacitive transducers (Paoletti et al., 1996).

The major advantage of gyroscopes is that the angular velocity remain the same no matter where the gyroscope is attached on a body segment, as long as its sensitive axis is parallel to the axis of rotation (Tong & Granat, 1999). Besides, unlike accelerometers, the gyroscope signal does not include gravitational component, which makes it easier to be interpreted.

However, compared with accelerometers, there are also some drawbacks associated with gyroscopes, such as more power consumption, higher price, more significant drifting problem, and being sensitive to shock (K Aminian & Najafi, 2004). Several methods have been developed to solve the drifting problem either by filtering the signal to eliminate the drifting component (Luinge et al., 1999; Miyazaki, 1997) or by resetting the signal based on expected values (Williamson & Andrews, 2001). In general, gyroscopes have not been utilized as widely as accelerometers in human motion studies but the desired features of gyroscopes make it a promising tool for analyzing body movements and daily activities (K Aminian & Najafi, 2004).

A magnetometer is an instrument that measures the strength and/or direction of the magnetic field in the vicinity of the instrument (Daniel Roetenberg, 2006). Magnetometers are typically used to assess sensor orientation (Bonnet & Heliot, 2007). They can also correct the drifting of accelerometer or gyroscope signals, thus increasing the measurement accuracy (D. Roetenberg et al., 2005). Furthermore, the direction of the magnetic field assessed by magnetometers can be used to separate the inertial component of the accelerometer signal from the gravitational component (Bonnet & Heliot, 2007). However, in practice, the measurement of the earth's magnetic field is easy to be affected by nearby ferrous materials in the environment (Zhu & Zhou, 2004) or local magnetic field generated by electronic devices typically equipped in a motion lab (De Vries et al., 2009). Therefore the orientation measured by magnetometers, if in a standalone format, should be used with caution.

2.4.2. Gait analysis with IMUs

In general, gait analysis with IMUs looks into details of the gait performance, such as critical events during a gait cycle, temporal parameters and spatial parameters of gait. Willemsen et al. (1990) conducted a study to detect critical events during a gait cycle with accelerometers attached between ankle and knee joints. Using cross correlation algorithms, they were able to detect stance phase and swing phase of walking. The accuracy of push-off detection was high (only two errors in more than one hundred steps), but the heel-strike detection was less accurate. Following the initial study, methods to assess temporal gait parameters with IMU sensors have been extensively investigated. For example, Tong and Granat (1999) demonstrated that with gyroscopes placed on the shank and the thigh, a variety of temporal gait parameters could be assessed by simply identifying critical data points (e.g. a single positive peak) in the angular velocity or angle profile. Aminian et al. (1999) used accelerations in the sagittal plane measured by two uniaxial accelerometers attached slightly above knee articulations to detect phases in a gait cycle. In general, although issues such as signal drifting have not been fully solved, by using appropriate filtering techniques and event detection algorithms, the overall accuracy of IMU sensors in terms of assessing temporal gait parameters appears sufficient for most motion studies (Mayagoitia et al., 2002).

The assessment of spatial gait parameters generally requires more complex algorithms. One method for estimating spatial parameters from IMU measurements is to establish regression models. For example, Meijer et al. (1991) demonstrated that signals of the accelerometers attached at the lower back reflected walking speed in an exponential way. However, the numerical relationship was not discussed in detail in their study. Later, Moe-Nilssen (1998) proposed a quadratic regression algorithm to estimate walking speed from the root mean square (RMS) of accelerations measured by a triaxial accelerometer at a reference point over the lumbar spine. Using a similar quadratic regression model, Henriksen et al. (2004) further investigated the test–retest reliability of trunk accelerometers in estimating gait parameters including step length, stride length and cadence. Measurement errors in their study were 0.009 m for step length, 0.022 m for stride length and 1.644 step/min for cadence.

Another method to estimate spatial parameters from IMU measurements is based on physical or biomechanical models. For instance, Miyazaki (1997) developed a simple gait model to estimate stride length from extended leg length and the angle between two legs. The angle between two legs was computed by integration of the angular velocity measured by a gyroscope attached on the thigh of one leg in the sagittal plane. A relative error within 15% was achieved. Zijlstra and Hof (1997) proposed an inverted pendulum model that utilized the vertical displacement of the whole body CoM to predict step length. CoM vertical displacement was computed by double integration of the CoM vertical acceleration measured by an accelerometer (Wiebren Zijlstra & Hof, 2003). Results in their studies showed that step length and walking speed were underestimated under both treadmill and overground walking conditions. However, with a multiplication factor of 1.25, differences between the predicted speed and measured speed were controlled within 16% for treadmill walking and 15% for overground walking. A more complicated double-segment gait model using both shank and thigh kinematics was proposed by Aminian et al. (2002). In this model, the swing phase was described as a double pendulum and the stance phase was considered as an inverse double pendulum.

Rotation angles of the lower limbs during stance phase and swing phase were computed by integration of the angular velocity, and used to estimate stride length and walking velocity. Errors for stride length and walking velocity were 0.07 m and 0.06 m/s respectively.

Typically, integration of acceleration and angular rate measured by IMUs need to be used with caution because of noise and drifting issues. However, in certain cases direct integration method can also be used. For example, Sabatini et al. (2005) conducted a study to estimate spatial gait parameters from the strapdown integration. With an auto-resetting scheme to remove signal drifting, RMS errors less than 0.18 km/h for walking speed and 1.52% for incline were achieved. Therefore, although integration algorithms are subject to accumulated errors, they remain to be a useful method for estimating spatial parameters.

2.4.3. Fall risk assessment with IMUs

With the development of the IMU technology, researchers have started to utilize IMUs to study the fall risk by measuring activity level, posture transitions, static and dynamic stability, and spatio-temporal gait characteristics (Johansen et al., 2000; Lockhart & Liu, 2008; Najafi et al., 2001; Najafi et al., 2002a). Traditionally, assessment of these parameters was restricted in motion labs because of cumbersome motion capture instruments. The utilization of IMUs makes it possible to measure these parameters in a free-living environment, thus greatly improves user compliance and offers possibility of long term monitoring.

Najafi, Aminian and their colleagues conducted a series of studies to assess the fall risk by gyroscopes and accelerometers. In 2001, they developed a gyroscope system for gait analysis and demonstrated the application of this system in assessing fall risk among older adults (Najafi et al., 2001). Later, they incorporated wavelet algorithms into the system for estimating temporal gait parameters (K. Aminian et al., 2002) and posture transition rate (Najafi et al., 2002a). A biomechanical model for spatial gait parameters estimation with gyroscopes was developed as well (K. Aminian et al., 2002). In general, they suggested that the IMU assessed gait parameters could formalize a diagnostic tool for abnormal gait analysis and fall risk estimation (K Aminian & Najafi, 2004). Furthermore, when used together with a portable data logger, the IMU system showed the potential to assess a large number of daily activity features continuously, thus allowing outdoor and long term fall risk monitoring (K Aminian & Najafi, 2004).

Another group also investigated ambulatory monitoring with IMU systems for assessing fall risk (M. J. Mathie et al., 2004; Merryn J Mathie et al., 2004). Parameters assessed in their studies include: energy expenditure, physical activities, balance and posture sway, gait, and posture transition. Based on these parameters, they proposed three modes of operation that can be used to assess the fall risk. They are: clinical assessment, event monitoring and longitude monitoring. The authors further suggested that it was possible to integrate these different modes of operation into one single accelerometry system (Merryn J Mathie et al., 2004).

Although the possibility of a portable fall risk assessment system was demonstrated in the studies discussed above, these studies mainly focused on the configuration of IMU hardware and the design of IMU software, but not the relationship between IMU assessments and fall risk. Recently, Giansanti et al. (2006) proposed a clinical tool that employed both accelerometers and gyroscopes for fall risk assessment. The designed neural network algorithm achieved a high sensitivity in discriminating the fall history group and the healthy younger group. Later, the authors defined four levels of fall risk (from level 1 - no fall risk to level 4 - major fall risk) with IMU measurements. They integrated the IMU system with the Global System for Mobile communication (GSM) network. Their objective is to furnish this tool along with a homecare device for daily routine monitoring of motion activity, and to eventually integrate it with other systems designed to monitor other physiological parameters during daily living (Giansanti et al., 2009).

In conclusion, with the development of technologies in the last few decades, methods have become available for using miniature IMUs assess fall risk (Scanaill et al., 2006; W. Zijlstra & Aminian, 2007). Current challenges for applying these methods include the optimal solutions of sensor configuration, and the design of specific IMU algorithm for fall risk assessment (W. Zijlstra & Aminian, 2007).

3. STUDY I: DETERMINANTS OF GAIT IN DIFFERENT AGE GROUPS AND THE ASSOCIATED SLIP AND FALL RISK

3.1. Objective

Older adults are generally considered to have higher slip and fall risk than young adults (Lockhart et al., 2005). However, slip and fall risk among older adults may vary as well. To further specify fall prone elderly from the general older adults group and provide them with appropriate interventions, effective fall risk assessments become essential.

Having people walk on a slippery surface and observe their occurrence of fall is a valid way to determine their slip and fall risk. However, this method is cumbersome and with potential risk of injury. If other parameters that can be measured in a much safer approach also have significant difference between fallers and non-fallers in a certain age group, they can be utilized to identify fall-prone people in this age group without introducing the potential risk of injury. As introduced in the first chapter, determinants of gait (DoG) parameters during normal walking could possibly be good slip and fall risk predictors because they reflect CoM vertical transition performance, which could further affect the severity of a slip. However, such relationship has not been explicitly studied. Therefore, this study was designed to investigate the age related differences in DoG parameters and how DoG parameters are related to slip and fall risk in different age groups. Since a slip occurs shortly after a heel contact, DoG parameters at the moment of heel contact were selected as the main focus for this investigation.

Two hypotheses of this study were:

Hypothesis 1-a: Older adults have significantly different DoG parameters at heel contact than young adults.

Hypothesis 1-b: Older fallers (i.e. older subjects who fell on a controlled slippery surface) have significantly different DoG parameters at heel contact than older non-fallers (i.e. older subjects who didn't fall on the same slippery surface).

3.2. Methods

3.2.1. Subjects

Twelve gender balanced older adults (65-84 years old) and twelve gender balanced young adults (18-30 years old) participated in this study. Subjects in both age groups were in general health condition. Exclusion criteria of the recruitment were: 1) cardiovascular problems, 2) respiratory problems, 3) neurological problems, 4) musculoskeletal problems, and 5) allergy or sensitivity to the adhesive tape used to affix retro-reflective markers. For safety consideration, adults older than 84 were not recruited for this study because statistics showed that they had much more severe consequences of fall than adults 65-84 (CDC, 2006, 2009b).

Table 3 summarized subjects' demographic information.

Table 3: Means (standard deviations) of subjects' demographic information

Group	Number of subjects and gender	Age (years old)	Height (cm)	Weight (kg)
Old	6 males, 6 females	75.9 (5.7)	166.1 (8.7)	75.9 (17.5)
Young	6 males, 6 females	25.1 (2.2)	171.9 (8.8)	69.4 (12.2)

3.2.2. Apparatus

A six-camera optoelectronic motion capture system (ProReflex, Qualisys AB, Gothenburg, Sweden) with twenty-six retro-reflective markers at body landmarks was used to collect kinematic data for this study. Two force plates (Bertec K80102, Type 4550-08, Bertec Corporation, OH, USA) were used to collect kinetic data. Both cameras and force plates sampled at 100 Hz frequency. A LabVIEW (National Instruments, Austin, TX) program was used to control data collection and synchronize measurements from the motion capture system and the two force plates. During the experiment, sleeveless shirts, shorts and sports shoes were provided to the subjects to minimize the interference of clothing.

3.2.3. Experiment

An over-ground walking experiment on both regular floor surface and slippery floor surface was conducted. Both young and older subjects were asked to walk on a linear, vinyl walkway (1.5 m by 15.5 m) back and forth, with an overhead harness system protecting them from potential falls. A television was placed at each end of the walkway. Subjects were required to look straight at the television while walking and walk as normal as possible during the entire experiment session. When subjects arrived at one end of the walkway, they were asked not to turn around until instructed to.

Prior to data collection, subjects were given ten minutes to get accommodated to the harness system (Liu & Lockhart, 2006). After that, subjects were asked to walk at two specified pace respectively. The first pace was the subject's normal walking pace and the second was 120% of the subject's normal pace. Data of ten walking trials (i.e. walking from one end of the walkway to the other end) was collected for each walking pace. Within the ten trials, an unexpected slip was induced by replacing a piece of dry floor surface in the middle of the walkway with slippery surface without the subject's awareness.

In addition, each subject was assessed by two standard fall risk assessments. The first one was the Morse Fall Scale (MFS) (J.M. Morse et al., 1989) and the second one was the Get-up and Go test (GUG) (Mathias et al., 1986).

3.2.4. Parameters computation

For each walking pace, three random non-slip trials and the one slip trial were selected for analysis. The specific footstep occurred in the area where the slippery floor was hidden/presented was analyzed for each selected trial. Prior to the computation of any parameters, motion capture system data was filtered by a Butterworth 4th order zero-lag low-pass filter with the cut-off frequency at 6 Hz (Lockhart et al., 2003). Force plate data was used without filtering. The following parameters were computed for this study.

<u>(i) Position, velocity and acceleration of markers of the motion capture system</u>

The instantaneous position (p_i) of an individual marker at moment i was read directly from the motion capture system measurement. The instantaneous velocity (v_i), acceleration (a_i) and jerk (j_i, the derivative of acceleration) can be derived using the following equations (Chaffin et al., 2006).

$$v_i = \frac{p_{i+1} - p_{i-1}}{2\Delta t} \quad \text{Equation 1}$$

$$a_i = \frac{v_{i+1} - v_{i-1}}{2\Delta t} \quad \text{Equation 2}$$

$$j_i = \frac{a_{i+1} - a_{i-1}}{2\Delta t} \quad \text{Equation 3}$$

where Δt is the time between two consecutive samples.

<u>(ii) Determinants of gait parameters</u>

Six 2-D determinants of gait parameters for the non-slip trials were computed using marker data from the motion capture system as the following:

Pelvic rotation angle (θ_{PR}) was computed as the horizontal angle between the frontal plane and the line segment between right ASIS marker and left ASIS marker.

Pelvic tilt angle (θ_{PT}) was computed as the vertical angle between the horizontal plane and the line segment between right ASIS marker and left ASIS marker.

Knee flexion angle (θ_{KF}) was computed as 180 degrees (representing neutral angle of knee joint) less the actual knee joint angle, where knee joint angle was computed as the angle between thigh (i.e. line segment between hip marker and knee marker) and shank (i.e. line segment between knee marker and ankle marker).

Ankle extension/flexion ($\theta_{AE/F}$) angle was computed as the actual ankle joint angle less 90 degrees (representing neutral angle of ankle joint), where ankle joint angle was computed as the angle between shank (i.e. line segment between knee marker and ankle marker) and instep (i.e. line segment between ankle marker and big toe marker). Positive values of θ_{PR} indicate ankle extension and negative values of θ_{PR} indicate ankle flexion.

Foot rotation angle (θ_{FR}) was computed as the angle between sole (i.e. line segment between heel marker and little toe marker) and the ground.

Pelvic lateral displacement (d_{PL}) was computed as the distance between the vertical axis and the intermediate point of right ASIS marker and left ASIS marker.

Figure 9 demonstrated the six determinants of gait parameters as discussed above.

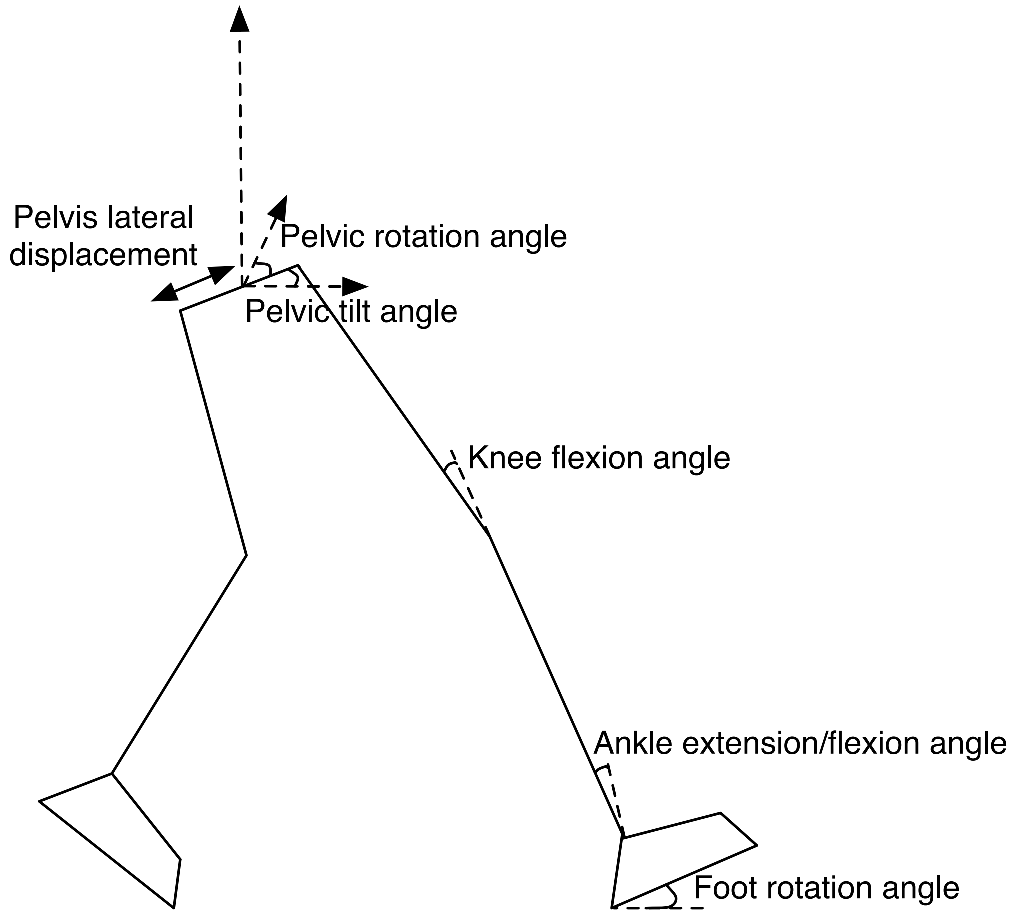


Figure 9: Demonstration of six determinants of gait parameters

<u>(iii) CoM vertical transition characteristics</u>

A whole body biomechanical model using twenty-six retro-reflective markers as defined in a study by Lockhart et al. (2003) was adopted to determine the whole body center of mass (CoM). CoM vertical displacement (d_{CoM}), velocity (v_{CoM}), acceleration (a_{CoM}) and jerk (j_{CoM}) during the non-slip trials were computed to represent CoM vertical transition performance.

(iv) Step duration, step length and walking velocity

To compute step duration and step length during the non-slip trials, the heel contacting moment need to be identified first. In this study, heel contacting moment (t_{HC}) was defined as the moment when the vertical GRF measured by the force plate exceeded 7 N (Lockhart & Kim, 2006). Based on that, step duration (t_{Step}) was computed as the time elapse between two consecutive heel contacts and step length (l_{Step}) was computed as the distance between one heel marker at one heel contacting moment and the other heel marker at the next heel contacting moment. Walking velocity of this step (v_{Walk}) was computed as l_{Step}/t_{Step}.

(v) Slip initiation severity measures

Three measures during the slip trials were selected to represent slip initiation severity. They were: (a) friction demand of a step as specified by the required coefficient of friction (rCOF), (b) heel contact velocity (HCV), and (c) initial slip distance in the slip initiation phase (SDI).

The required coefficient of friction (rCOF) was defined as the third peak of the ratio of the vertical component of the ground reaction force to the horizontal component of the ground reaction force (Perkins & Wilson, 1983). Heel contact velocity (HCV) was defined as the heel marker instantaneous velocity at t_{HC}. Initial slip distance (SDI) was defined as the distance that the heel marker travelled from the moment when the antero-posterior acceleration of the heel marker of the slipping foot (a_{HEEL}^{AP}) changed from negative to positive (anterior being the positive direction) to the moment when a_{HEEL}^{AP} reached its maximum.

3.2.5. Statistical analysis

(i) ANCOVA test on the hypotheses of this study

To test the two hypotheses of this study, analysis of covariance (ANCOVA) test was performed. Independent variables of this analysis were age (young and old), and subjects' occurrence of fall while stepping on the slippery surface (fallers and non-fallers). Dependent variables of this analysis were the six DoG parameters at heel contact including pelvic rotation angle (θ_{PR}), pelvic tilt angle (θ_{PT}), knee flexion angle (θ_{KF}), ankle extension/flexion angle ($\theta_{AE/F}$), foot rotation angle (θ_{FR}), and pelvis lateral displacement (d_{PL}). Differences in DoG parameters at heel contact between young and old, fallers and non-fallers were investigated. Walking velocity (v_{Walk}) was considered as the covariate in this study.

The statistical model of the ANCOVA can be described as the following:

$$Y_{ijkl} = \mu + \alpha_i + \beta_j + \gamma x_{ij} + \varepsilon_{ijk} \qquad \text{Equation 4}$$

where Y_{ijkl} represents a dependent variable; μ is the population mean of this variable (e.g. pelvic rotation angle at heel contact); α represents the effect of factor A (i.e. young or old); β represents the effect of factor B (i.e. faller or non-faller); γ represents the effect of covariate x (i.e. walking velocity); and ε represents the random error of a specific trial.

A significance level of $\alpha \leq 0.05$ was used to determine the significance of difference for the ANCOVA test.

For comparison, differences in the two standard fall risk assessments (MFS and GU&G) between young and old, fallers and non-fallers were also investigated using the analysis of variance (ANOVA) method. The same significance level ($\alpha \leq 0.05$) was used for the ANOVA test as well. Among the six DoG parameters and the two standard fall risk assessments, the ones that showed significant difference between fallers and non-fallers were considered as good fall risk predictors.

(ii) Linear correlation between DoG parameters, CoM vertical transition characteristics, and slip initiation severity measures

For the DoG parameters that were found to have significant differences between fallers and non-fallers, their relationship with CoM vertical transition characteristics and slip initiation severity parameters were investigated. The relationship was characterized by the Pearson's correlation coefficient, which represented the linear correlation between two measures. The purpose of this investigation was to provide further insight into the question that why certain DoG parameters appeared be good fall risk predictors.

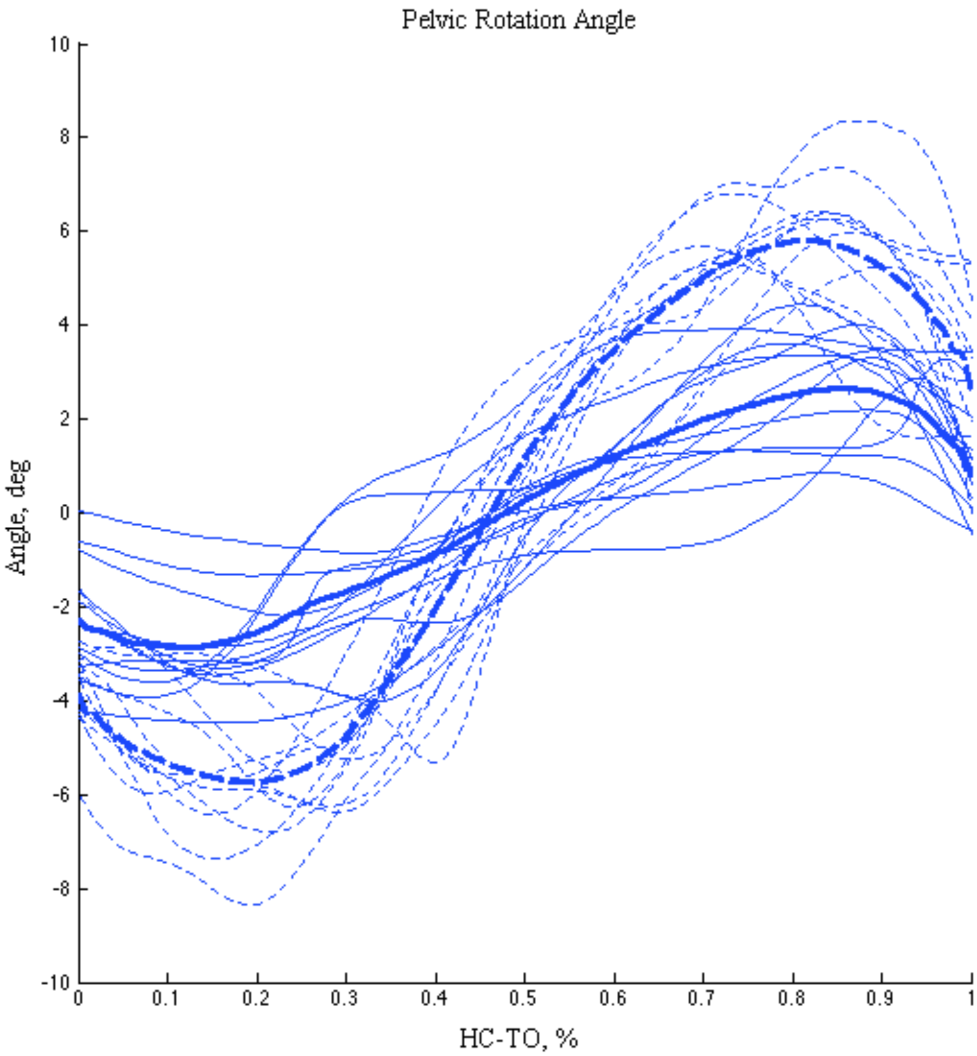
3.3. Results

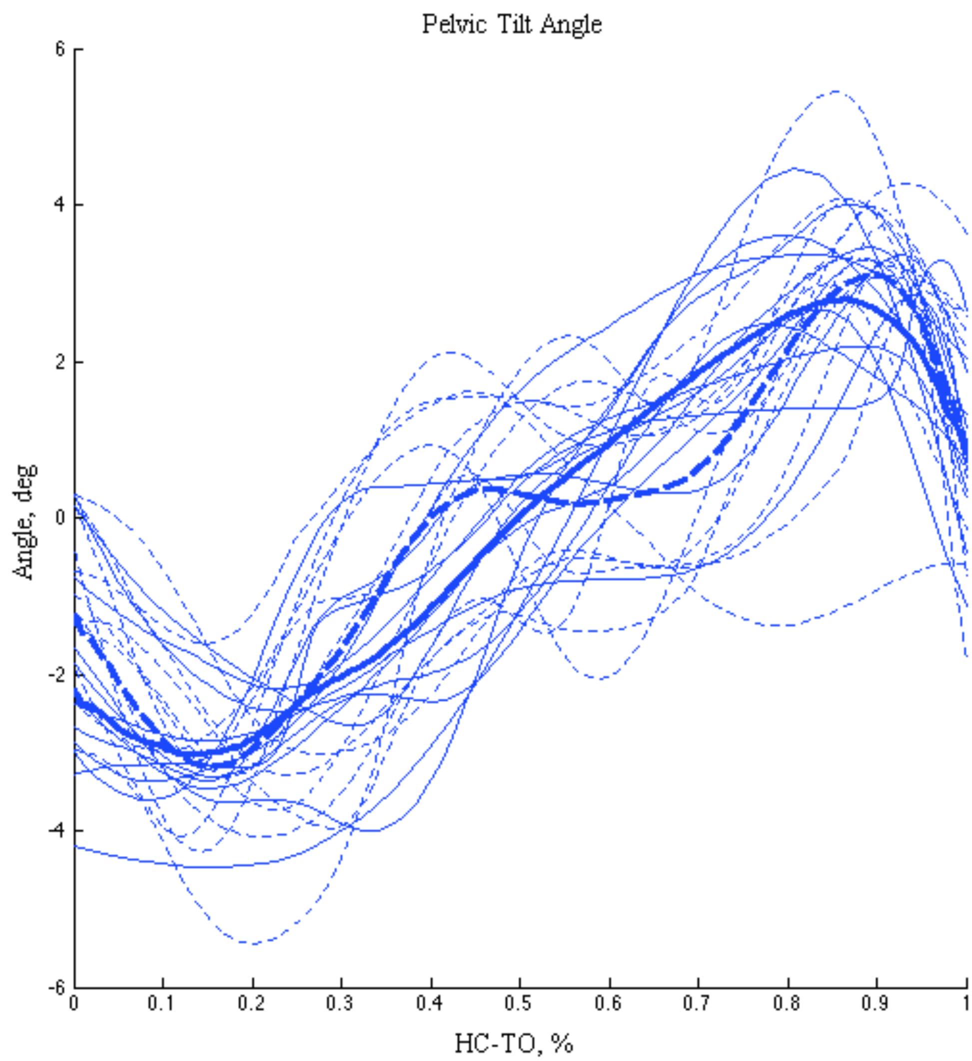
3.3.1. Identifying fallers and non-fallers by actual occurrence of fall

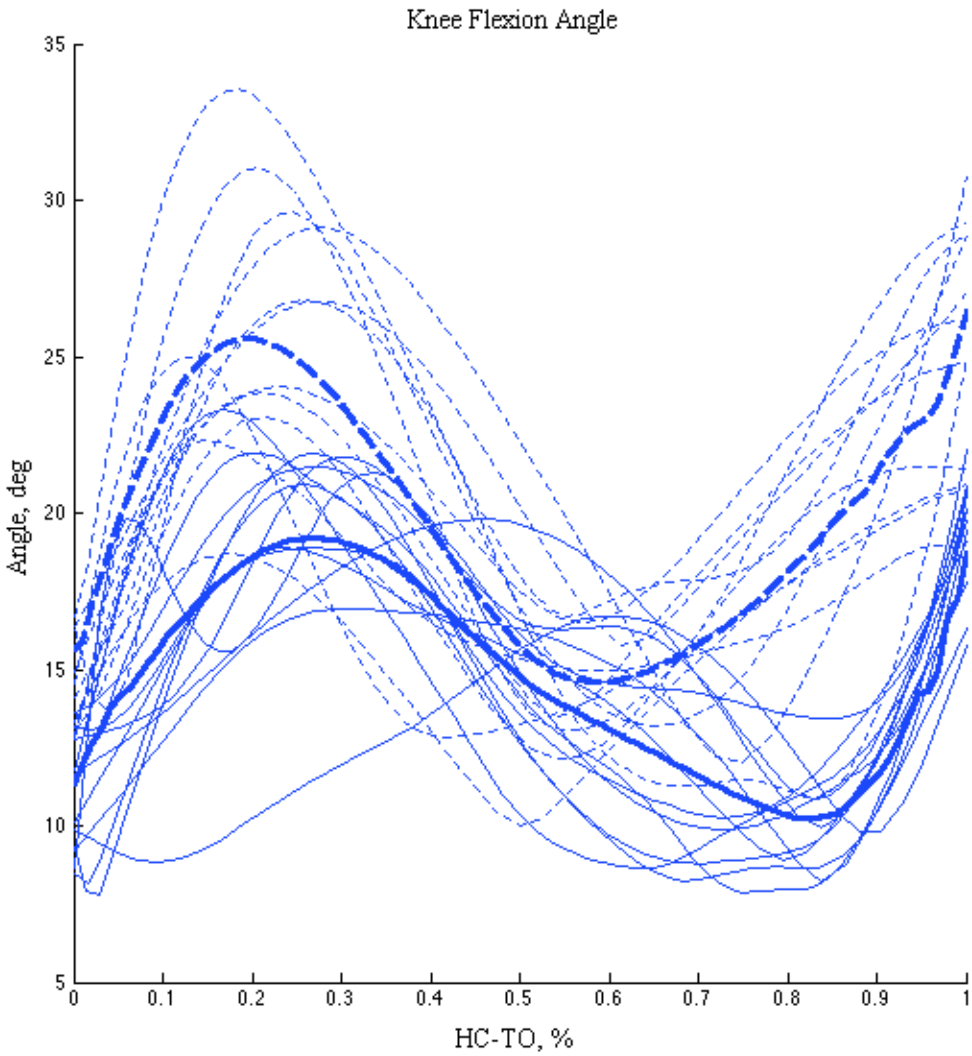
The gold standard to identify fallers and non-fallers in this study was the occurrence of fall when the subject walked over the slippery surface without awareness of the hazard. Within the twenty-four subjects, five young adults and seven older adults slipped and fell (caught by the harness) at least once during the experiment. They were considered as fallers. The other seven young adults and five older adults, however, had only slight slip and were able to maintain their balance and walk across the slippery surface. They were considered as non-fallers.

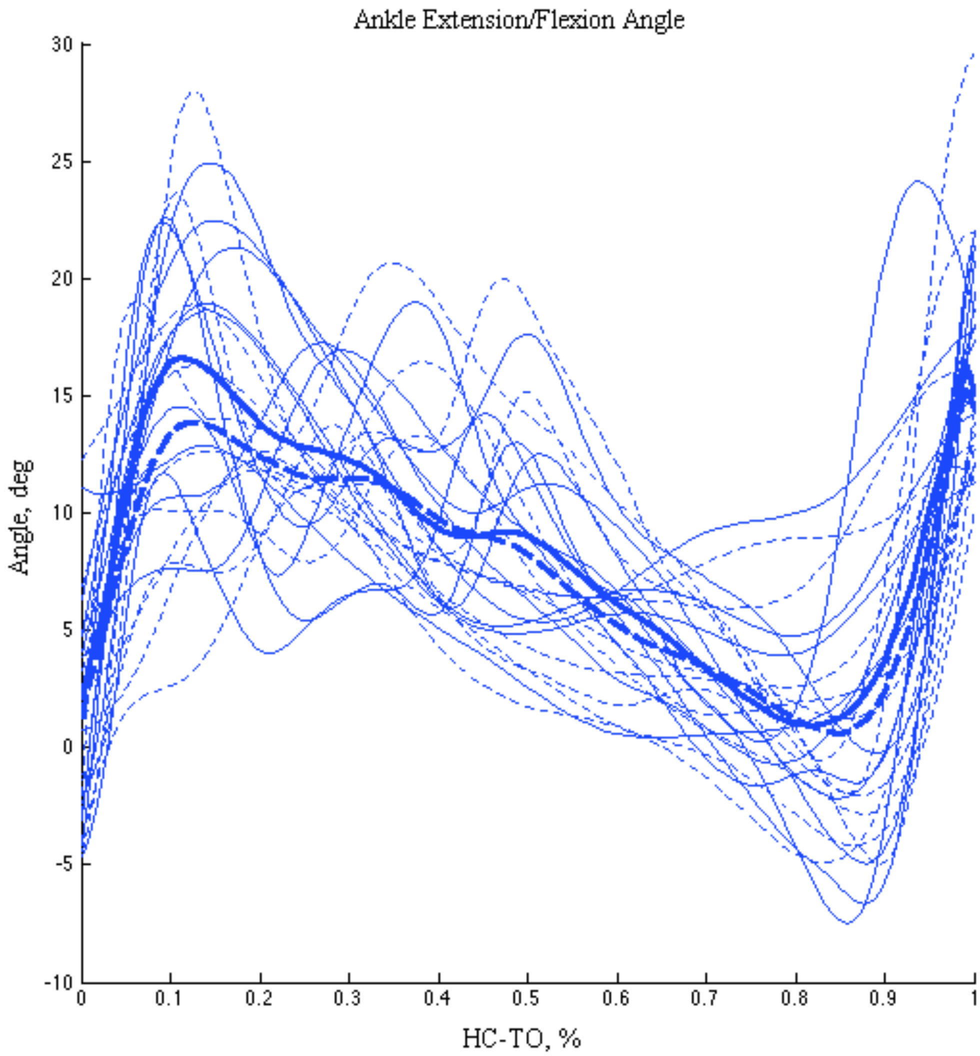
3.3.2. DoG parameters for fallers and non-fallers in different age groups

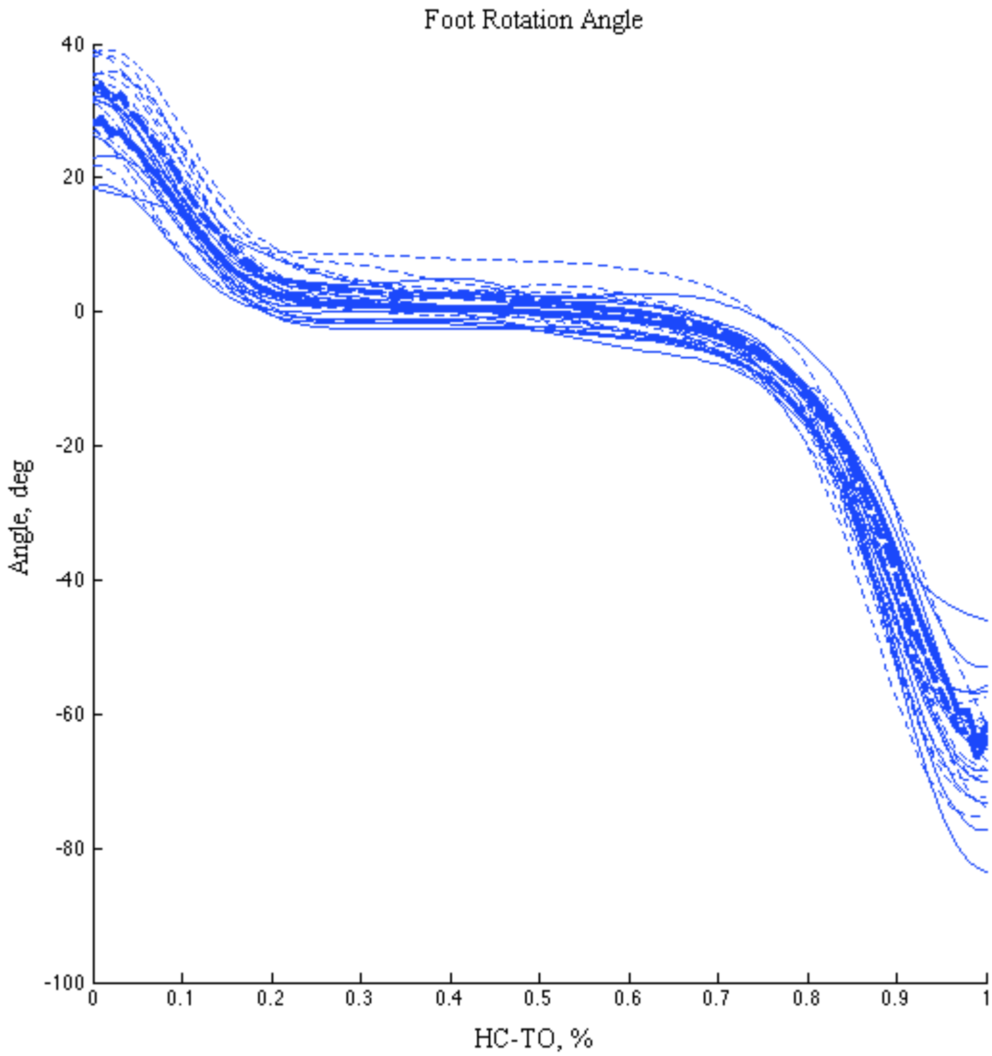
To provide an overview of the profiles of the six DoG parameters computed in this study, DoG parameters in a stance phase (i.e. from heel contact to toe off) were plotted in Figure 10. For the purpose of demonstration, one normal walking trail from each subject was selected.


Pelvic Rotation Angle
Angle, deg
HC-TO, %
10
8
6
4
2
0
-2
-4
-6
-8
-10
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1


Pelvic Tilt Angle
Angle, deg
HC-TO, %
6
4
2
0
-2
-4
-6
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1


Knee Flexion Angle
Angle, deg
HC-TO, %
35
30
25
20
15
10
5
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1


Ankle Extension/Flexion Angle
Angle, deg
HC-TO, %
30
25
20
15
10
5
0
-5
-10
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1


Foot Rotation Angle
40
20
0
-20
-40
-60
-80
-100
Angle, deg
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
HC-TO, %

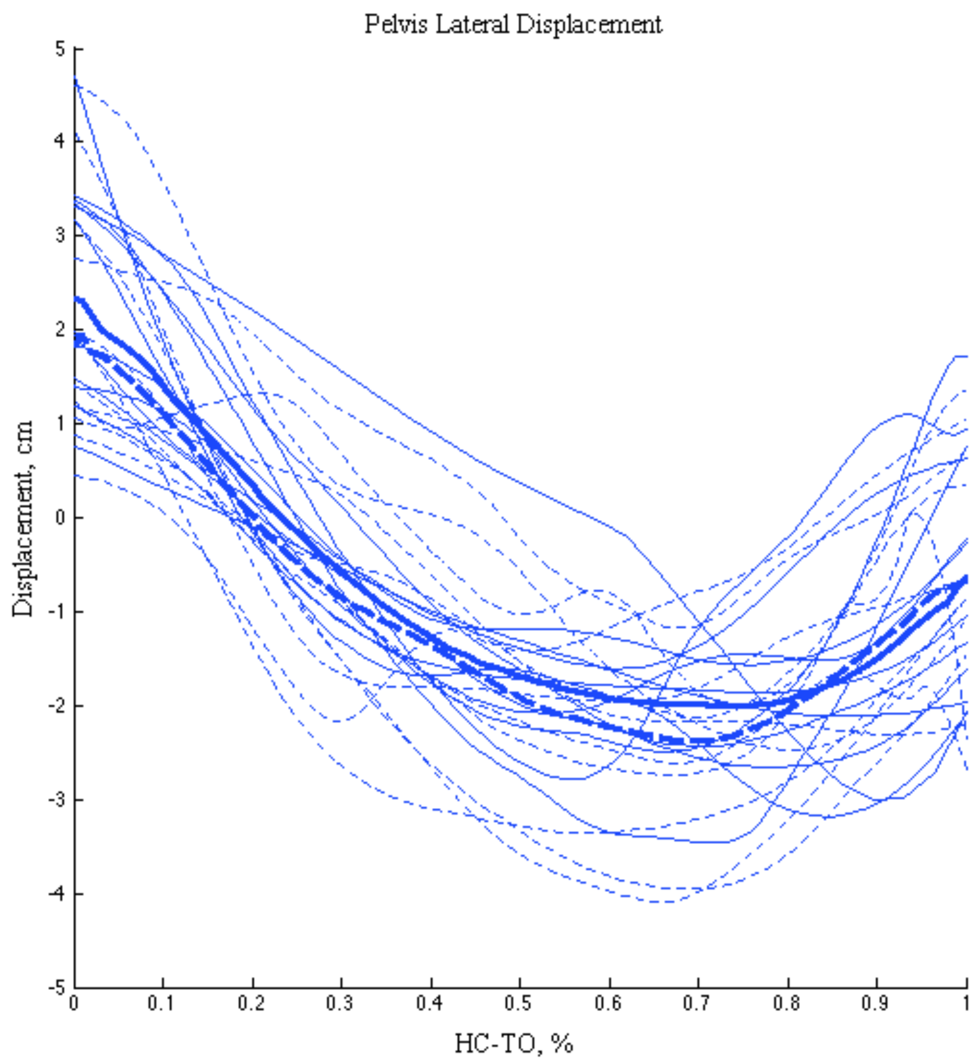


Figure 10: Example of six DoG parameters from heel contact to toe off

(dashed lines – young; solid lines – old; bold lines – ensemble average for each age group)

At the moment of heel contact, older adults were found to have significantly different θ_{PR} ($p = 0.0328$) from young adults. Difference in θ_{KF} between older adults and young adults was marginally significant ($p = 0.0528$). However, difference in θ_{PT}, $\theta_{AE/F}$, θ_{FR} or d_{PL} between age groups was not significant. Across all subjects, fallers were found to have significantly different θ_{PR} ($p = 0.0003$) and θ_{KF} ($p = 0.0005$) from non-fallers. No significant interaction between age and occurrence of fall was found for θ_{PR} or θ_{KF}. In the faller and non-faller comparison, older subjects contributed to the major part of the observed difference. When breaking it down for each age group, only older fallers were found to have significantly different θ_{PR} ($p = 0.0023$) and θ_{KF} ($p = 0.0065$) from older non-fallers. The difference in θ_{PR} and θ_{KF} for young fallers and non-fallers was not significant ($p = 0.1241$ for θ_{PR} and $p = 0.1209$ for θ_{KF}). .

Table 4 summarized fallers' and non-fallers' DoG parameters at heel contact for both young and old groups.

Table 4: Means (standard deviations) of fallers' and non-fallers' DoG parameters at heel contact in different age groups

Parameter	Young		Old		
	Non-faller	Faller	Non-faller	Faller	
$\theta_{PR}\ (deg)$	5.5 (1.1)	4.5 (1.7)	**5.3 (1.3)**	**3.5 (1.2)**	*
$\theta_{PT}\ (deg)$	1.5 (0.9)	1.7 (1.2)	1.5 (0.8)	1.7 (1.1)	
$\theta_{KF}\ (deg)$	16.3 (6.5)	12.5 (4.2)	**15.1 (8.4)**	**7.2 (4.5)**	*
$\theta_{AE/F}\ (deg)$	6.5 (2.7)	7.1 (3.7)	6.4 (3.2)	6.2 (2.9)	
$\theta_{FR}\ (deg)$	28.4 (4.2)	28.1 (5.4)	30.5 (4.7)	30.9 (5.2)	
$d_{PL}\ (cm)$	3.2 (0.7)	3.2 (0.5)	3.2 (0.7)	3.1 (1.0)	

Significant differences marked with *

3.3.3. Standard fall risk assessments for fallers and non-fallers in different age groups

$t_{GU\&G}$ was found to have significant difference between young and old ($p = 0.0003$), but no significant difference between fallers and non-fallers for either age group. No significant difference was found for MFS score either between young and old, or between fallers and non-fallers. Table 5 summarized the results from the standard fall risk assessments.

Table 5: Means (standard deviations) of fallers' and non-fallers' standard fall risk assessment results in different age groups

Parameter	Young		Old	
	Non-faller	Faller	Non-faller	Faller
MFS	4 (9)	5 (11)	6 (11)	3 (9)
$t_{GU\&G}$ (s)	6.2 (0.7)	7.1 (0.6)	8.4 (1.5)	7.5 (1.1)

3.3.4. Relationship between DoG parameters, CoM vertical transition characteristics, and slip initiation severity measures

Figure 11 demonstrated the whole body CoM transition trajectory during normal walking. The trajectory was computed from the marker data of the motion capture system. It can be seen clearly that CoM transit along an arched pathway during normal walking, with a significant vertical displacement for each gait cycle.

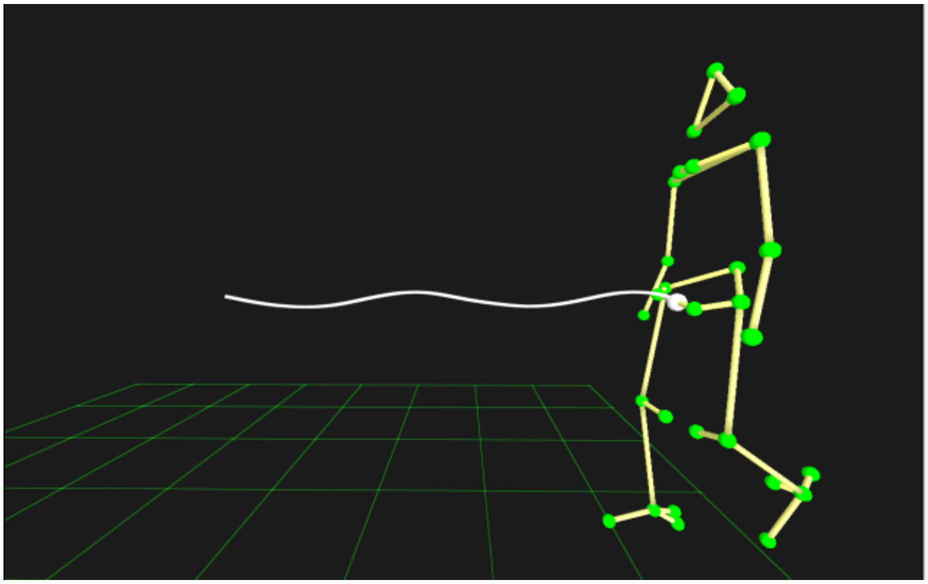


Figure 11: CoM transition profile during normal walking

For old adults, at the moment of heel contact, CoM vertical velocity (v_{CoM}) was found to have moderate correlation with pelvic rotation angle (θ_{PR}) ($r = -0.5795$). CoM vertical acceleration (a_{CoM}) was found to have moderate correlation with pelvic rotation angle (θ_{PR}) ($r = -0.4939$) and knee flexion angle (θ_{KF}) ($r = -0.4600$). CoM vertical jerk (j_{CoM}) was found to have moderate correlation with pelvic rotation angle (θ_{PR}) ($r = -0.6755$) and knee flexion angle (θ_{KF}) ($r = -0.4273$). For young adults, however, there was no significant correlation between CoM vertical transition characteristics and DoG parameters at heel contact.

Among the three slip initiation severity measures ($rCOF$, HCV, and SDI), slip distance I (SDI) of young subjects was found to have moderate correlation with v_{CoM} ($r = 0.5292$) and a_{CoM} ($r = 0.4741$), while SDI of old subjects was found to have moderate correlation with v_{CoM} ($r = 0.5233$), a_{CoM} ($r = 0.6318$), and j_{CoM} ($r = 0.4225$). Furthermore, SDI of old subjects was also found to have moderate correlation with θ_{PR} ($r = -0.4612$) and θ_{KF} ($r = -0.4582$). Table 6 and Table 7 summarized all the correlation coefficient between each two parameters that were investigated in this study.

Table 6: Correlation matrix for selected DoG parameters, CoM vertical transition characteristics and slip initiation severity measures for young adults

	$rCOF$	HCV	SDI	θ_{PR}	θ_{KF}	d_{CoM}	v_{CoM}	a_{CoM}	j_{CoM}
$rCOF$	1.0000	0.1638	-0.0328	**0.4031**	0.3956	-0.1830	0.2119	0.1795	-0.2303
HCV		1.0000	0.3847	-0.0114	-0.0688	-0.1069	0.3613	0.2648	-0.0038
SDI			1.0000	-0.1819	0.1104	0.0021	**0.5292**	**0.4741**	0.1196
θ_{PR}				1.0000	0.3998	-0.1504	-0.0023	-0.0256	-0.0299
θ_{KF}					1.0000	-0.3463	-0.1973	-0.0419	-0.3924
d_{CoM}						1.0000	0.3300	0.3809	0.1266
v_{CoM}							1.0000	**0.6989**	0.1323
a_{CoM}								1.0000	0.0473
j_{CoM}									1.0000

Table 7: Correlation matrix for selected DoG parameters, CoM vertical transition characteristics and slip initiation severity measures for older adults

	$rCOF$	HCV	SDI	θ_{PR}	θ_{KF}	d_{CoM}	v_{CoM}	a_{CoM}	j_{CoM}
$rCOF$	1.0000	**0.5042**	-0.1081	-0.1900	-0.2290	0.1373	0.1420	-0.0703	0.2004
HCV		1.0000	0.3145	**-0.4727**	**-0.5067**	0.2395	-0.0249	0.0814	0.3183
SDI			1.0000	**-0.4612**	**-0.4582**	-0.0765	**0.5233**	**0.6318**	**0.4225**
θ_{PR}				1.0000	**0.6719**	-0.3026	**-0.5795**	**-0.4939**	**-0.6755**
θ_{KF}					1.0000	-0.1983	-0.3505	**-0.4600**	**-0.4273**
d_{CoM}						1.0000	0.0248	-0.1747	0.3003
v_{CoM}							1.0000	**0.8254**	**0.4554**
a_{CoM}								1.0000	0.2437
j_{CoM}									1.000

3.4. Discussion

3.4.1. Major findings of this study

The main objective of this study was to investigate the differences in DoG parameters between fallers and non-fallers in different age groups, so as to determine if certain DoG parameters can be used to predict slip and fall risk. For the older age group, it was found that pelvic rotation angle at heel contact (θ_{PR}) and knee flexion angle at heel contact (θ_{KF}) were significantly different between fallers and non-fallers. Therefore, these two parameters appeared to be potential slip and fall risk predictors for older adults. However, none of the DoG parameters showed significant difference between fallers and non-fallers for the young group, indicating that young adults' slip and fall risk may not be well predicted by their determinants of gait.

3.4.2. How do DoG parameters affect slip and fall risk: a theoretical analysis

The assumption behind selecting certain DoG parameters as slip and fall risk predictor is that: the existence of DoGs reduces the whole body CoM vertical transition in a gait cycle and smoothens the CoM transition pathway (Murray et al., 1964), while the shortened and smoothened CoM pathway can further help to reduce slip initiation severity by affecting lower extremity dynamics. This assumption was verified by the correlations between DoG parameters, CoM vertical transition characteristics, and slip initiation severity measures that were computed in this study. The following analysis provides further insights into the relationship from a theoretical point of view.

(i) Pelvic rotation and slip and fall risk

Compared with a compass gait with the same step length, the presence of pelvic rotation reduces the vertical displacement of CoM by elevating the lowest position of CoM in a gait cycle (Inman et al., 1981; Perry, 1992). In Figure 12, CoM vertical displacement without pelvic rotation (h_0) and with pelvic rotation (h_1) can be expressed as:

$$h_0 = L - \sqrt{L^2 - \left(\frac{SL}{2}\right)^2} \quad \text{Equation 5}$$

$$h_1 = L - \sqrt{L^2 - \left(\frac{SL-l_0}{2}\right)^2} \quad \text{Equation 6}$$

where L is the length of the leg, SL is the step length, and l_0 is the displacement of pelvis in the direction of progression.

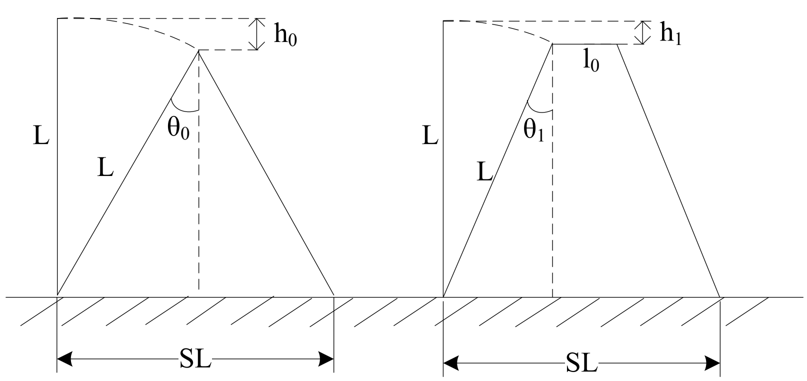


Figure 12: CoM vertical displacement without (left) and with (right) pelvic rotation

In the above equations, l_0 can be substituted by the product of pelvic rotation angle (θ_{PR}) and the width of the pelvis (W_{pelvis}):

$$l_0 = W_{pelvis} \cdot sin\ (\theta_{PR}) \quad \text{Equation 7}$$

Therefore, the reduction in CoM vertical displacement due to pelvic rotation is:

$$\Delta h_{PR} = \sqrt{L^2 - \left(\frac{SL - W_{pelvis} \cdot sin\,(\theta_{PR})}{2}\right)^2} - \sqrt{L^2 - \left(\frac{SL}{2}\right)^2} \qquad \text{Equation 8}$$

At the moment of heel contact, the whole body CoM is travelling in the forward and downward direction (Lockhart et al., 2003), and is approaching the lowest position of CoM at double support. As computed above, with pelvic rotation, the lowest CoM position is elevated by the length of Δh_{PR}. This means that the whole body CoM has less vertical distance to travel at the moment of heel contact, as compared with a compass gait without pelvic rotation. A reduced distance to travel requires a reduced velocity. Therefore, the larger the pelvic rotation is, the shorter vertical distance the CoM needs to travel from heel contact to double support, and the smaller the CoM vertical velocity (v_{CoM}) will be.

In a normal gait, the horizontal component of the CoM velocity contributes to the forward movement of CoM, whereas the vertical component of the CoM velocity draws the CoM backwards. Since the essence of keeping dynamic balance during walking is to effectively transit the body mass in the direction of progression (Winter, 1995a), a reduced CoM vertical velocity can be beneficial. As analyzed previously, the presence of pelvic rotation reduces CoM vertical velocity at heel contact. Therefore, it may help to transit CoM more effectively and therefore help maintain body balance after heel contact and recover from an initial slip.

<u>(ii) Knee flexion and slip and fall risk</u>

The presence of knee flexion at heel contact reduces the leg angle with reference to a vertical plane. As can be seen from Figure 13, the relationship between the leg angle without knee flexion (θ_0) and the leg angle with knee flexion (θ_1) can be expressed as:

$$\theta_1 = \theta_0 - \theta \qquad \text{Equation 9}$$

where θ is the knee flexion angle.

The tangent of the leg angle as illustrated in Figure 13 represents the ratio of the horizontal GRF to the vertical GRF. This ratio is typically referred to as the required coefficient of friction (rCOF) and it is a parameter to represent the friction demand for keeping balance during walking (Grönqvist et al., 1989; Perkins, 1978). The smaller the rCOF is, the less likely a slip will occur. Therefore, a reduced leg angle at heel contact may reduce the risk of slip initiation as well.

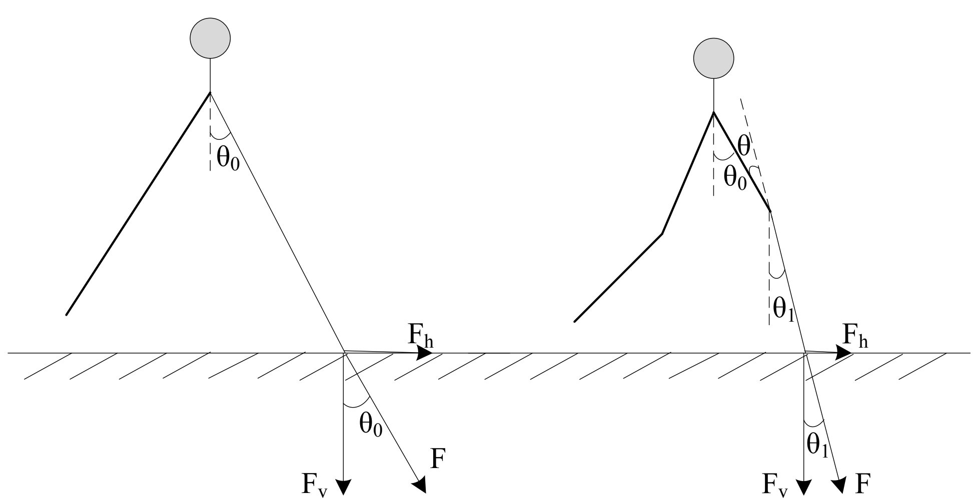


Figure 13: Leg angle without (left) and with (right) knee flexion

Knee flexion at heel contact not only reduces the leg angle, but also results in less jerky motion at the whole body CoM. From a kinetic point of view, jerk is proportional to the change of force. The presence of knee flexion at heel contact dampens the impact of heel contacting event. As a result, the ground reaction force caused by heel contacting applies to the whole body CoM more slowly. A slower change of force applied to CoM results in a smaller CoM jerk, which in turns leads to a smoother transition of CoM that can potentially increases walking stability (Devita & Skelly, 1992).

3.4.3. Age effects on the relationship between DoG parameters and slip and fall risk

Results in this study illustrated that older adults have smaller pelvic rotation and smaller knee flexion than the young adults. This is consistent with other studies that found decreased pelvic rotation and stiffer knee joints among the elderly (Elble et al., 1991; JudgeRoy et al., 1996; Murray et al., 1964). And this age difference can be used to explain the generally higher slip and fall risk among elderly (Lockhart et al., 2005). However, when looking at fallers and non-fallers from each age group, it was found that the linkage between DoG degradation and the occurrence of fall is much stronger in the old group than in their younger counterparts. One reason to explain this finding is that: for older adults, the ones who slip and fall tend to be the ones who have more severe gait degradation; while for young adults, gait degradation becomes a less prevalent factor for determining their occurrence of slip and fall.

Several existing studies have showed evidences that support this explanation explicitly or implicitly. For example, Talbot et al. (2005) did a large scale study on the cause of falling within 292 young adults, 616 mid-age adults, and 589 old adults. They found that older adults fell more frequently during ambulation while young adults fell more frequently during sports or exercise. Moreover, among the fallers, older adults fell mostly due to balance or gait impairment, while young adults fell mostly due to accidental or environmental factors. Another example is the study that Moyer et al. did on gait parameters as predictors of slip severity in younger and older adults (2006). They found that in general, greater step length normalized by leg length (SLR), and more rapid changing foot to floor angles at heel contact (FFA) were associated with higher slip severity. However, the fact that young adults could tolerate larger SLR and FFA than older adults suggested that gait characteristics seemed to play a more important role in determine the occurrence of slip and fall for older adults than for young adults. All these evidences have showed that the method of using gait characteristics to predict one's slip and fall risk might achieve better accuracy when applied to older adults than applied to young adults.

3.4.4. Comparison between DoG parameters and other fall risk assessments

In this study, the DoG method was compared with the Get-up & Go test in terms of their predictability. For the Get-up & Go test, results in this study suggested that the movement time ($t_{GU\&G}$) was only sensitive to age, but not the occurrence of slip and fall within each age group. It appeared that the Get-up & Go test was rather a tool to illustrate the general aging effect on walking speed, while DoG parameters provided further details on gait degradation to differentiate fallers and non-fallers. This finding agreed with several peer studies that also found the inadequacy of the Get-up & Go test in predicting falls. For example, Lindsay et al. (2004) have reported that the Get-up & Go test, used in isolation, was unable to identify those patients who were likely to fall among 160 old patients admitted to an acute hospital.

This study also compared the DoG method with the Morse Fall Scale. Results suggested that the total score of the Morse Fall Scale (MFS) was not discriminative in terms of identifying fallers and non-fallers in this study. This may be because that subjects recruited in this study were all healthy adults, whereas the MFS was targeted to patients in hospital or long term care places (J.M. Morse et al., 1989) and had generalization problems when applied to healthy community dwellers (O'Connell & Myers, 2002). As a result, almost all subjects, fallers or non-fallers, received a perfect MFS score in this study. The few outliers were spread between different age groups, thus were not informative at all.

In conclusion, findings in this study suggested that the DoG method could potentially be used as a screening tool for identifying individuals with higher slip and fall risk within a healthy old group. This DoG method appeared to have improved sensitivity than certain existing fall risk assessment tools, and could potentially provide more detailed diagnostic information in terms of gait degradation.

3.4.5. Limitation of current study

In this study, only snapshots of DoG parameters at heel contact were investigated in terms of their relationship with slip and fall risk. This was because that a slip was typically initiated shortly after a heel contact (Lockhart et al., 2003), therefore DoG kinematics at heel contact was considered to have the most direct effects on slip initiation. However, in a more general sense, gait characteristics at other moment of a gait cycle (e.g.

maximum angle of a DoG) may have indirect effects on the overall slip and fall risk as well, because they can represent other aspects of gait performance such as the overall CoM transition distance. Therefore, future study can add minimum, maximum, average, variation, and other statistics of the DoG profile in an entire gait cycle into the model, and investigate their relationship with slip and fall risk.

Furthermore, the current study only found significant difference between fallers and non-fallers in pelvic rotation and knee flexion. However, this may also due to the fact that the study was focused on DoG parameters at heel contact. Other DoGs, although didn't have significant difference at heel contact, may become important at other epochs of a gait cycle. Their relationship with slip and fall risk can be more implicit, but worth further investigation in order to better understand risk factors of a slip and fall.

Lastly, this study only attempted to relate DoG parameters with slip initiation severity measures. This was because after the initial slip period, other reactive recovery response kicked in. Reactive recovery strategies involve more upper extremity movements and the whole body coordination (Lockhart et al., 2005). It differs between individuals and age groups and goes beyond the scope of gait characteristics. By nature reactive recovery response cannot be fully explained / predicted by the DoG method. This is a shared limitation among all methods that use gait characteristics as the predictors for falls. Future study can investigate the combination of the DoG method and other posture control and dynamic stability methods, to establish a more comprehensive model for slip and fall risk assessment.

4. STUDY II: EFFECTS OF GAIT CONSTRAINTS ON DETERMINANTS OF GAIT AND THE ASSOCIATED SLIP AND FALL RISK

4.1. Objective

In the previous chapter, determinants of gait (DoG) were used to investigate the age related effects on slip and fall risk. Besides age, another important category of factors that could influence slip and fall risk is gait constraints (e.g. a knee brace). On one hand, gait constraints are necessary in certain circumstance for the purpose of protecting or immobilizing injured or weak joints and limbs. On the other hand, they can be risky in terms of increasing slip and fall risk because they alter normal gait (Cook et al., 1997). However, there wasn't sufficient research on the effects of gait constraints on gait pattern and slip and fall risk. Therefore, this study was designed to investigate effects of gait constraints on associated slip and fall risk by using the DoG concept. In specific, the knee brace and the arm sling were studied because both of them were commonly used gait constraints.

Two hypotheses in this study were:

Hypothesis 2-a: The use of knee brace has a significant effect on knee flexion at heel contact and slip initiation severity measures.

Hypothesis 2-b: The use of arm sling has a significant effect on pelvic rotation at heel contact and slip initiation severity measures.

4.2. Methods

4.2.1. Subjects

Ten male and ten female young adults (18-30 yrs) in general health condition participated in this study. Exclusion criteria for the recruitment were the same as Study I. Table 8 summarized subjects' demographic information.

Table 8: Means (standard deviations) of subjects' demographic information

Gender	No. of Subjects	Age (years)	Height (cm)	Weight (kg)
Male	10	26.2 (2.5)	179.4 (5.5)	78.8 (16.9)
Female	10	23.7 (2.1)	162.4 (4.9)	58.8 (6.9)

4.2.2. Apparatus

Study II used the same apparatus as in Study I for data collection.

4.2.3. Experiment

First, subjects were randomly divided into two groups, each group with five males and five females respectively. Demographic profiles of the two groups of subjects were compared and verified with no significant difference. An over-ground walking experiment was conducted. Subjects were asked to walk along the same regular floor surface and slippery floor surface as used in Study I with two specified walking condition respectively. The first walking condition was to walk normally without any gait constraint. The second walking condition was different for the two groups of subjects. The first group walked with a rigid knee brace worn at their preferred side. The knee brace held the knee at near 0° flexion position. The second group walked with their arms placed in an arm sling. The arm sling was anchored to the subject's trunk and fixed with Velcro straps to hold both arms at near 90° elbow flexion position and both wrists and shoulders at near 0° flexion/extension position. The same experiment procedure as Study I was followed. To minimize the learning effect, experiments of the normal walking condition and the constrained walking condition were scheduled with at least one-week interval in between for each subject. Sequence of the two walking conditions was also balanced among subjects.

4.2.4. Parameter computation

Methods for computing experiment variables were the same as Study I.

4.2.5. Statistical analysis

Analysis of variance (ANOVA) was performed to investigate the effects of gait constraints on DoG parameters at heel contact, CoM vertical transition characteristics at heel contact, and slip initiation severity measures. Independent variable of this study was the walking condition (normal walking – NW, constrained walking with knee brace – CK, and constrained walking with arm sling – CA). Dependent variables were: (a) DoG parameters at heel contact including pelvic rotation angle (θ_{PR}), pelvic tilt angle (θ_{PT}), knee flexion angle (θ_{KF}), ankle extension/flexion angle ($\theta_{AE/F}$), foot rotation angle ($\theta_{F\mathrm{R}}$), and pelvis lateral displacement (d_{PL}); (b) CoM vertical transition characteristics at heel contact including CoM vertical displacement (d_{CoM}^{v}), CoM vertical velocity (v_{CoM}^{v}), CoM vertical acceleration (a_{CoM}^{v}) and CoM vertical jerk (j_{CoM}^{v}); and (c) slip initiation severity measures including friction demand of a step as specified by the required coefficient of friction (rCOF), heel contact velocity (HCV), and initial slip distance in the slip initiation phase (SDI).

The statistical model of the ANOVA can be described as the following:

$$Y_{ij} = \mu + \alpha_i + \varepsilon_{j(i)} \qquad \text{Equation 10}$$

where Y_{ij} represents a dependent variable, μ is the population mean of this variable, α is the effect of a gait constraint, and $\varepsilon_{j(i)}$ is the random error of a specific trial.

Similar as Study I, a significance level of $\alpha \leq 0.05$ was used to determine the significance of difference.

4.3. Results

4.3.1. Effects of gait constraints on DoG parameters

Walking with a constrained knee by the rigid knee brace (i.e. walking condition CK) was found to have significant effect on θ_{KF} at the moment of heel contact ($p < 0.0001$). Post hoc analysis using Turkey's HSD method further suggested that the mean θ_{KF} with knee brace was significantly smaller than without knee brace. Effects of CK on θ_{AF} ($p = 0.0644$) and θ_{FR} ($p = 0.0586$) were marginally significant based on the selected significance level. No significant effect of CK was found on θ_{PR}, θ_{PT}, and d_{PL}.

Walking with constrained arms by the arm sling (i.e. walking condition CA) was found to have significant effect on θ_{PR} at the moment of heel contact ($p = 0.0003$). Post hoc analysis using Turkey's HSD method further suggested that the mean θ_{PR} with arm sling was significantly smaller than without arm sling. No significant effect of CA on other five DoGs was found.

Table 9 summarized means and standard deviations of subjects' DoG parameters at heel contact under constrained walking condition and normal walking condition.

Table 9: Means (standard deviations) of subjects' DoG parameters at heel contact under different walking conditions

Parameter	Subject Group 1			Subject Group 2		
	Normal Walking	CK Walking		Normal Walking	CA Walking	
$\theta_{PR}\ (deg)$	6.2 (1.5)	5.2 (1.5)		**6.0 (1.2)**	**3.8 (1.0)**	*
$\theta_{PT}\ (deg)$	1.6 (1.0)	1.5 (0.8)		2.0 (0.6)	2.1 (0.7)	
$\theta_{KF}\ (deg)$	**15.4 (4.1)**	**3.8 (1.2)**	*	13.1 (4.8)	13.6 (4.5)	
$\theta_{AE/F}\ (deg)$	7.0 (2.0)	8.8 (1.9)		9.0 (4.5)	6.4 (4.0)	
$\theta_{FR}\ (deg)$	26.3 (2.6)	29.1 (3.4)		26.3 (3.4)	26.1 (6.5)	
$d_{PL}\ (cm)$	3.2 (0.4)	3.8 (1.1)		2.9 (0.6)	2.8 (1.1)	

Significant differences marked with *

4.3.2. Effects of gait constraints on CoM vertical transition characteristics

The effect of CK was found to be significant on v_{CoM} ($p = 0.0277$), a_{CoM} ($p = 0.0088$) and j_{CoM} ($p = 0.0002$) at the moment of heel contact. The effect of CA was found to be significant on d_{CoM} ($p = 0.0483$), v_{CoM} ($p = 0.0030$), a_{CoM} ($p = 0.0294$) and j_{CoM} ($p = 0.0006$) at the moment of heel contact. Table 10 summarized means and standard deviations of subjects' CoM vertical transition characteristics at heel contact under constrained walking conditions and normal walking condition.

Table 10: Means (standard deviations) of subjects' CoM vertical transition characteristics at heel contact under different walking conditions

Parameter	Subject Group 1			Subject Group 2		
	Normal Walking	CK Walking		Normal Walking	CA Walking	
$d_{CoM}\ (cm)$	3.7 (1.3)	4.2 (1.0)		**3.1 (1.2)**	**4.1 (0.9)**	*
$v_{CoM}\ (cm/s)$	**15.9 (4.6)**	**22.0 (6.6)**	*	**15.3 (3.0)**	**26.5 (9.8)**	*
$a_{CoM}\ (g)$	**0.22 (0.05)**	**0.28 (0.04)**	*	**0.23 (0.04)**	**0.30 (0.08)**	*
$j_{CoM}\ (g/s)$	**0.0028 (0.0007)**	**0.0041 (0.0006)**	*	**0.0030 (0.0005)**	**0.0050 (0.0001)**	*

Significant differences marked with *

4.3.3. Changes in slip and fall risk due to gait constraints

For subject group 1, CK walking condition was found to have significantly different $rCOF$ ($p = 0.0165$) from normal walking. For subject group 2, CA walking condition was found to have significantly different HCV ($p < 0.0001$) and SDI ($p < 0.0001$). Table 11 summarized means and standard deviations of subjects' initial slip risk measures under constrained walking conditions and normal walking condition.

Table 11: Means (standard deviations) of subjects' slip initiation severity measures under different walking conditions

Parameter	Subject Group 1			Subject Group 2		
	Normal Walking	CK Walking		Normal Walking	CA Walking	
$rCOF$	**0.169 (0.011)**	**0.197 (0.032)**	*	0.177 (0.018)	0.178 (0.020)	
$HCV\ (cm/s)$	31.8 (8.8)	33.6 (10.7)		**21.1 (3.7)**	**35.0 (7.0)**	*
$SDI\ (cm)$	1.8 (0.8)	2.0 (0.9)		**1.7 (0.8)**	**3.5 (0.8)**	*

Significant differences marked with *

4.4. Discussion

4.4.1. Summary of major findings in this study

The main objective of this study was to investigate if the increased slip and fall risk due to gait constraints can be reasonably explained by the determinants of gait model. Findings from this study suggested that the knee constraint and the arm constraint did have significant effect on knee flexion and pelvic rotation respectively. Moreover, with these gait constraints, knee flexion and pelvic rotation changed in the way that would lead to larger CoM vertical transitions during a gait cycle. In theory, such relationship can be used to explain why certain gait constraints can increase slip and fall risk. In practice, it can also be used as a prediction tool to assess the risk of using gait constraints on potential slips and falls.

4.4.2. Effects of gait constraints on determinants of gait

It was found in this study that the use of a knee brace during walking reduced the knee flexion angle at heel contact. This is not difficult to understand because by design a knee brace limits the range of motion of the knee joint. Since flexion is the most significant movement of knee following heel contact (Morrison, 1970), it is not a surprise that the effect of knee brace manifested in terms of a smaller knee flexion angle at heel contact.

Admittedly, a knee brace may affect not only knee flexion, but also other determinants of gait. In this study, it was found that the ankle flexion and foot rotation were also moderately affected, whereas the other three DoGs, i.e., pelvic rotation, pelvic tilt, and pelvis lateral displacement, were less affected. Since knee flexion, ankle flexion and foot rotation are all movements in the sagittal plane but the other three DoGs exist in other reference planes orthogonal to the sagittal plane, it indicates that a knee brace may mostly influence movements in the sagittal plane, but might be less concerned for movements happened in other reference planes.

Compared with a knee brace, the effects of an arm sling on DoGs can be more complex because the arm sling does not apply direct constraints on any lower extremity joints. It was found in this study that the effects of using an arm sling were mostly on pelvic rotation. Pelvic rotation angle with the arm sling was significantly smaller than without the arm sling. Empirically, such a result matches findings from literature. For example, Jackson et al. (1983) found that restricted arm swing during walking, either voluntarily held at the side or fixed to the trunk with bandages, reduced torso rotations about the vertical axis. Ford et al. (2007) also reported that the reduction of pelvic rotation due to arm constraint was significant in their study.

Besides evidence from peer studies, the relationship between arm constraint and pelvic rotation can be further explained by the following shoulder-spine-pelvis rotation model. Firstly, bones from the shoulder girdle to the pelvis formalize a capital “I” shape. The two arms, as pendulums suspended at both ends of the shoulder girdle, facilitate the shoulder rotation by helping the transformation between kinetic energy and potential energy (Inman, 1966). In other words, within a certain range, the larger the arm swing is, the easier the shoulder girdle can rotate. Therefore, if arm swing is restricted, the shoulder rotation is reduced (Jackson et al., 1983). Reduced shoulder rotation is further associated with reduced pelvic rotation. This is because the shoulder-spine-pelvis structure twists back and forth within a gait cycle. Shoulder rotation at the upper girdle of the “I beam” structure and pelvic rotation at the lower girdle of the “I beam” structure counter balance each other (Stokes et al., 1989; Townsend, 1981). Therefore, if the shoulder rotation is limited, counteractive rotation at the pelvis, i.e. pelvic rotation, should reduce as well in order to maintain trunk orientation and stability. In a summary, restricted arm swing causes less shoulder rotation; less shoulder rotation further results in less pelvic rotation. Such a chain effect may explain the reduction of pelvic rotation found in this study.

Similar to the knee constraint, arm constraint not only reduces pelvic rotation, but may also affect other DoGs. However, results from this study suggested that the effects of arm constraint on other DoGs might manifest themselves at other epochs of a gait cycle. When limiting the investigation at the moment of heel contact, only pelvic rotation appeared to be affected significantly. Furthermore, arm constraint can also alter upper body reactive recovery movements once a slip is initiated. However, detailed analysis on slip and fall events suggested that the onset of arm reaction typically occurred 50 ms after the slipping heel reached its maximum velocity (Lockhart, 2008). Since the current study mainly focused on the slip initiation risk, only the factors that could possibly affect slip initiation were studied. The effect of arm constraints on DoGs and upper body reactive recovery movement which happens at later stages of a gait cycle / slip event were not included in the current investigation.

4.4.3. Using the DoG method to explain the effects of gait constrains on slip and fall risk

Understanding how pelvic rotation and knee flexion were affected by certain gait constraints wasn't the ultimate goal of this study. One more important question is that: can the changes of pelvic rotation and knee flexion due to gait constraints effectively explain how the slip and fall risk is affected by gait constraints? Intuitively, walking with gait constraints could increase the slip and fall risk because the gait constraints alter the normal gait pattern. This assumption was also confirmed by the observed higher friction demand ($rCOF$) and more severe slip initiation (HCV and SDI) among the subjects when they walked with gait constraints. However, such an effect caused by gait constraints may not be sufficiently explained by simple gait parameters such as step length and walking speed. For example, Table 12 summarized means and standard deviations of step length (l_{step}) and walking speed ($v_{walking}$) for normal walking and walking with the knee brace. ANOVA analysis on the data suggested that there was no significant difference in step length and walking speed between normal walking and walking with constrained knee.

Therefore, these common gait parameters were not very useful for the purpose of this study. More detailed gait characteristics than step length and walking speed were needed for analyzing the effects of gait constraints.

Table 12: Means (standard deviations) of subjects' common gait parameters under normal walking condition and constrained knee condition

	Normal Walking	CK Walking
l_{step} (m)	0.775 (0.063)	0.745 (0.067)
$v_{walking}$ (m/s)	1.47 (0.52)	1.57 (0.39)

The above result inspired the idea of using the DoG method to explain the effects of gait constrains on slip and fall risk because the DoG model describes gait in more detail than the common gait parameters. As analyzed in previous study, if a certain DoG changes in the way that results in larger CoM vertical displacement, higher CoM vertical velocity, acceleration and jerk, this change can be considered related to more severe slip initiation. In this study, gait constraints were found to cause smaller knee flexion and pelvic rotation at heel contact. Results on CoM vertical transition characteristics also confirmed that CoM vertical transition did change in the direction that agreed with the theoretical analysis. Therefore, the current study can be considered as another evidence supporting the DoG method for slip and fall risk assessment.

4.4.4. Limitation of current study

Similar to Study I, the effects of gait constraints on determinants of gait were only limited at the moment of heel contact. As a result, the two DoGs being affected the most were found to be pelvic rotation and knee flexion. Other DoGs were less affected at heel contact. However, it is entirely possible that when looking at other events in a gait cycle such as double support or takeoff, effects of certain gait constraints on other DoGs can become dominant. These effects can be investigated in the future following a similar procedure demonstrated in the current study.

Secondly, gait constraints not only affect gait kinematics, but also affect other aspects of walking such as the ground reaction force, ankle torque, upper body reactive recovery strategies and etc. It is important to understand that the objective of the current study was to explore if DoG parameters at heel contact can be used to reasonably explain the relationship between certain gait constraints and the slip initiation risk. It by no means indicates that changes in DoGs at heel contact are the only effect that the gait constraints can introduce. Other effects caused by gait constrains can also be critical to later stages of a slip and fall event, and worth to be investigated in future studies.

5. STUDY III: ASSESSING DETERMINANTS OF GAIT AND THE ASSOCIATED SLIP AND FALL RISK BY INERTIAL MEASUREMENT UNITS

5.1. Objective

The previous chapters have suggested that, degradation (due to aging) or altering (due to gait constraints) of pelvic rotation and knee flexion can change certain slip initiation severity measures, and therefore affect slip and fall risk. However, the previous studies utilized optoelectronic motion capture system to measure DoGs. This system is expensive and not portable, thus has limited application. The objective of this study was to investigate the feasibility of using miniature inertial measurement units (IMUs) as an alternative to the optoelectronic system. Representative IMU measurements for pelvic rotation and knee flexion at heel contact were studied and used to differentiate walking conditions / groups with different slip and fall risk. The IMU solution can greatly expand the usage of the findings in previous chapters, and can be implemented at very low cost for various environments such as clinics and nursing homes.

Two hypotheses of this study were:

Hypothesis 3-a: IMU measurements for pelvic rotation and knee flexion at heel contact are able to differentiate constraint walking and normal walking.

Hypothesis 3-b: IMU measurements for pelvic rotation and knee flexion at heel contact are able to differentiate fallers and non-fallers for different age groups.

5.2. Methods

5.2.1. Apparatus

In Study I and II, an inertial measurement system (XM-B, Xsens Technologies B.V., Pantheon, Netherlands) was used to collect inertial motion data. The XM-B system is composed of (1) two MTx Motion Tracker that measures 3D accelerations and angular velocities, (2) an Xbus Master that supplies power to the MTx nodes, synchronizes each note, and buffers the raw signal, and (3) a WR-A Bluetooth Receiver that receives the real time data and transfers the data to a host (PC or PDA). Table 13 summarizes specifications of the MTx node. The sampling frequency was select at 100Hz for this study.

Table 13: Specifications of the MTx node

Sensor performance	Angular velocity	Acceleration
Dimensions	3 axes	3 axes
Full Scale (standard)	± 1200 deg/s^2	± 50 m/s^2
Linearity	0.1% of FS	0.2% of FS
Bias	1 deg/s	0.02 m/s^2
Noise	0.05 deg/s/√Hz	0.002 m/s^2/√Hz
Alignment error	0.1 deg	0.1 deg
Bandwidth	40 Hz	30 Hz
Max update rate	512 Hz	512 Hz

The two MTx nodes were attached in the following locations respectively: (1) Node 1 on top of the subject's right anterior superior iliac spine (R-ASIS); and (2) Node 2 in the middle of the right shank facing lateral (Figure 14).

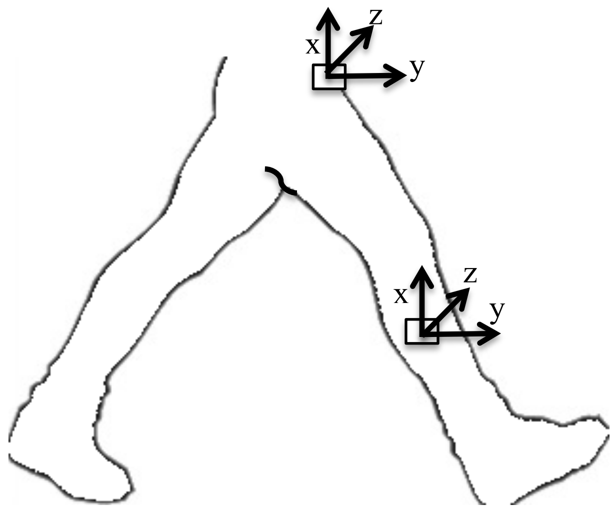


Figure 14: IMU placement and its local coordinate system

5.2.2. Selecting IMU parameters of interest

The two IMU nodes provided twelve different raw signals: acceleration in x, y, z axis of Node 1 and 2, and angular velocity around x, y, z axis of Node 1 and 2. Prior to any analysis, signals were filtered by a Butterworth 4th order zero-lag low-pass filter with a cut-off frequency of 10 Hz. After that, the following four parameters were selected as representative inertial parameters for pelvic rotation and knee flexion.

Acceleration in z axis of Node 1 (a^{z}_{R-ASIS}): this vector is in the same direction as the pelvic rotation direction in the horizontal plane. It was selected to represent the change of linear velocity at one end of the pelvis when pelvis rotates.

Angular velocity around x axis of Node 1 (ω^{x}_{R-ASIS}): this vector was selected to represent pelvic rotation speed in the horizontal plane.

Resultant acceleration in x axis and y axis of Node 2 ($a_{R-Shank}^{XY}$): this vector was selected to represent the change of linear velocity at the middle of the shank caused by knee flexion.

Angular velocity around z axis of Node 2 ($\omega_{R-Shank}^{z}$): this vector was selected to represent shank rotation speed caused by knee flexion.

5.2.3. Determining heel contact by acceleration

Similar as previous chapters, instantaneous values of the above four parameters at heel contact were used to assess slip initiation risk. However, previous studies used the vertical ground reaction force (GRF_v) measured by a force plate to determine heel contact moment, which did no apply to this study. Instead of force plate, this study used the filtered vertical acceleration signal at R-ASIS (a_{R-ASIS}^{x}) to help determine heel contact. By overlapping GRF_v and a_{R-ASIS}^{x} on the same plot with the same time scale, it was found that a major local minimum right before a single major local maximum in the a_{R-ASIS}^{x} signal concurred with the heel contact moment detected by GRF_v (Figure 15). Therefore, this peak on a_{R-ASIS}^{x} was selected to represent heel contact moment.

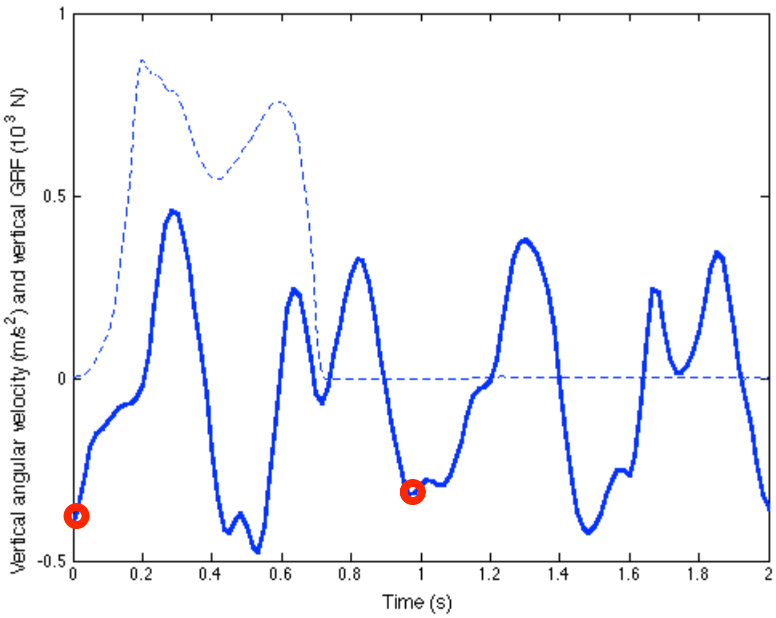


Figure 15: Heel contact detected by R-ASIS vertical acceleration

(dashed line - GRF_v; solid line - a^x_{R-ASIS}; circles - heel contacts)

5.2.4. Linear discriminant analysis

Linear discriminant analysis (LDA) was used to differentiate normal walking and constrained walking. LDA is a common method used in statistics and pattern recognition. In general, it takes a set of features that can characterize two or more classes, and finds the linear combination of these features that best separate the classes. The resulting linear combination model is referred to as a "classifier" (McLachlan, 2004).

A classifier is first developed from a training data set. The training data set can be expressed by an N-by-K matrix M. Each row in the matrix is an observation and each column in the matrix is a feature. The value of element M_{nk} is determined by:

$M_{nk} = 1$ if observation n is from class k;

$M_{nk} = 0$ if observation n is not from class k.

With training data set M, the classifier (linear combination of features) is developed so as to minimize the expected cost of misclassification:

$$\hat{y} = argmin_{y=1,\dots,K} \sum_{k=1}^{K} \hat{P}(k|x)C(y|k) \qquad \text{Equation 11}$$

where $\hat{y}$ is the predicted classification; $\hat{P}(k|x)$ is the posterior probability of class k for observation x; and $C(y|k)$ is the cost of classifying an observation as y when its true class is k (The MathWorks, 2013). In this study, it was assumed that the cost of misclassifying an observation in class k is identical across all K classes.

After the classifier is developed, it can be validated by a validation data set. The error of this classifier can be represented by the percentage of misclassification in the validation data set:

$$error = \frac{number\ of\ misclassified\ observations}{number\ of\ observations} \times 100\% \qquad \text{Equation 12}$$

For establishing LDA model for normal walking and constrained walking, one walking trial from each subject for each walking condition (i.e. normal walking and constrained walking) was randomly selected as the training data. Instantaneous values of $\mathrm{a}^{\mathrm{z}}_{\mathrm{R-ASIS}}$, $\omega^{\mathrm{x}}_{\mathrm{R-ASIS}}$, $\mathrm{a}^{\mathrm{XY}}_{\mathrm{R-Shank}}$ and $\omega^{\mathrm{z}}_{\mathrm{R-Shank}}$ at heel contact were used as the four features of each data point. Another walking trial from each subject for each walking condition was randomly selected as the validation data.

For establishing LDA model for fallers and non-fallers, one walking trial from each subject in each age group (i.e. young and old) was randomly selected as the training data. The same four features as above were used to develop the LDA model. Another walking trial from each subject in each age group was randomly selected as the validation data.

5.3. Results

5.3.1. Differentiating normal walking and walking with constrained arm

Instantaneous values of the four selected IMU parameters at heel contact were used as the input features for the LDA model. The four-dimensional feature map was difficult to visualize. Therefore, for the purpose of demonstration, Figure 16 plotted two features, a^{z}_{R-ASIS} and ω^{x}_{R-ASIS}, for both normal walking (NW) trials in the training data set and walking with constrained arm (CA) trails in the training data set. The objective of LDA was to find the best linear boundary that separates NW walking and CA walking on this feature map.

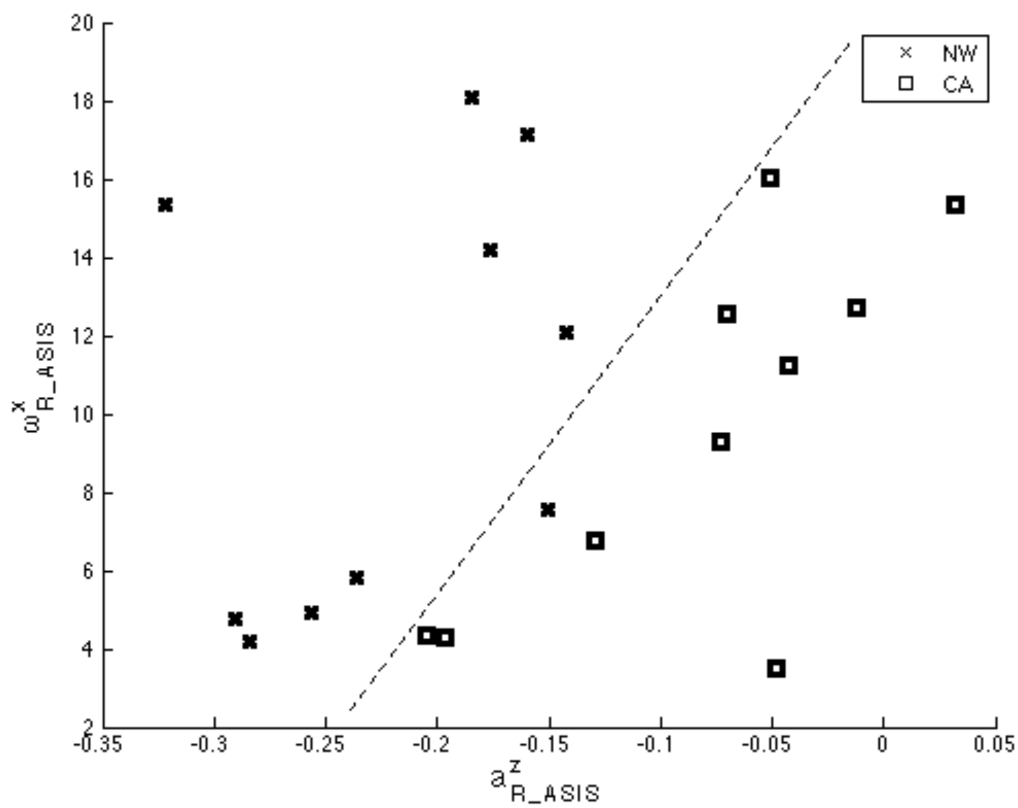


Figure 16: 2-D feature map for normal walking (NW) and constrained arm walking (CA)

The classification boundary (classifier) derived from the given training data set can be expressed as:

$$54.3a^{z}_{R-ASIS} - 0.4\omega^{x}_{R-ASIS} - 14.9a^{XY}_{R-Shank} - 0.01\omega^{z}_{R-Shank} + 28.2 = 0$$

Equation 13

The performance of this classifier when used to classify the validation data set was fairly good. Nine out of ten NW trials and seven out of ten CA trials in the validation data set were classified correctly. The overall error of this classifier was 20%.

5.3.2. Differentiating normal walking and walking with constrained knee

Figure 17 plotted two features, $a^{XY}_{R-Shank}$ and $\omega^{z}_{R-Shank}$, for both normal walking (NW) trials in the training data set and walking with constrained knee (CK) trails in the training data set.

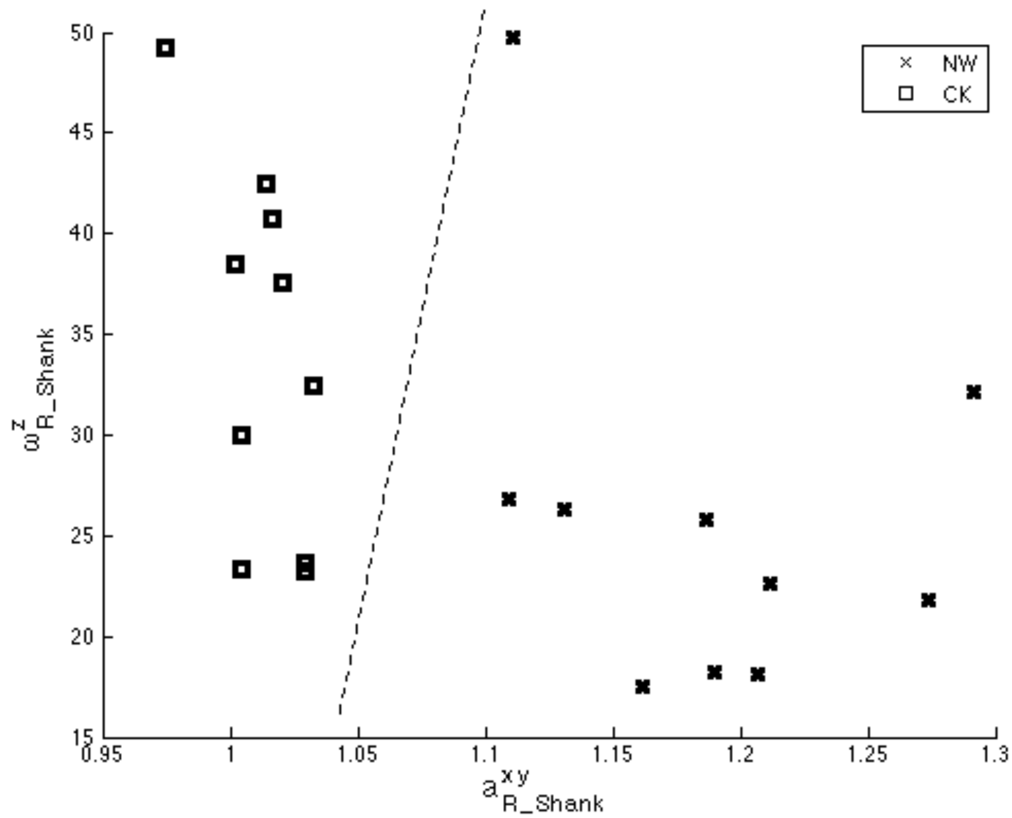


Figure 17: 2-D feature map for normal walking (NW) and constrained knee walking (CK)

The classification boundary (classifier) derived from the given training data set can be expressed as:

$$63.0a^{z}_{R-ASIS} - 1.6\omega^{x}_{R-ASIS} + 139.0a^{XY}_{R-Shank} + 0.2\omega^{z}_{R-Shank} - 135.1 = 0$$

Equation 14

The performance of this classifier when used to classify the validation data set was fairly good. Seven out of ten NW trials and nine out of ten CK trials in the validation data set were classified correctly. The overall error of this classifier was 20%.

5.3.3. Differentiating fallers and non-fallers for both age groups

Figure 18 and Figure 19 plotted two features, a^{z}_{R-ASIS} and $a^{XY}_{R-Shank}$, for fallers and non-fallers in each age group respectively.

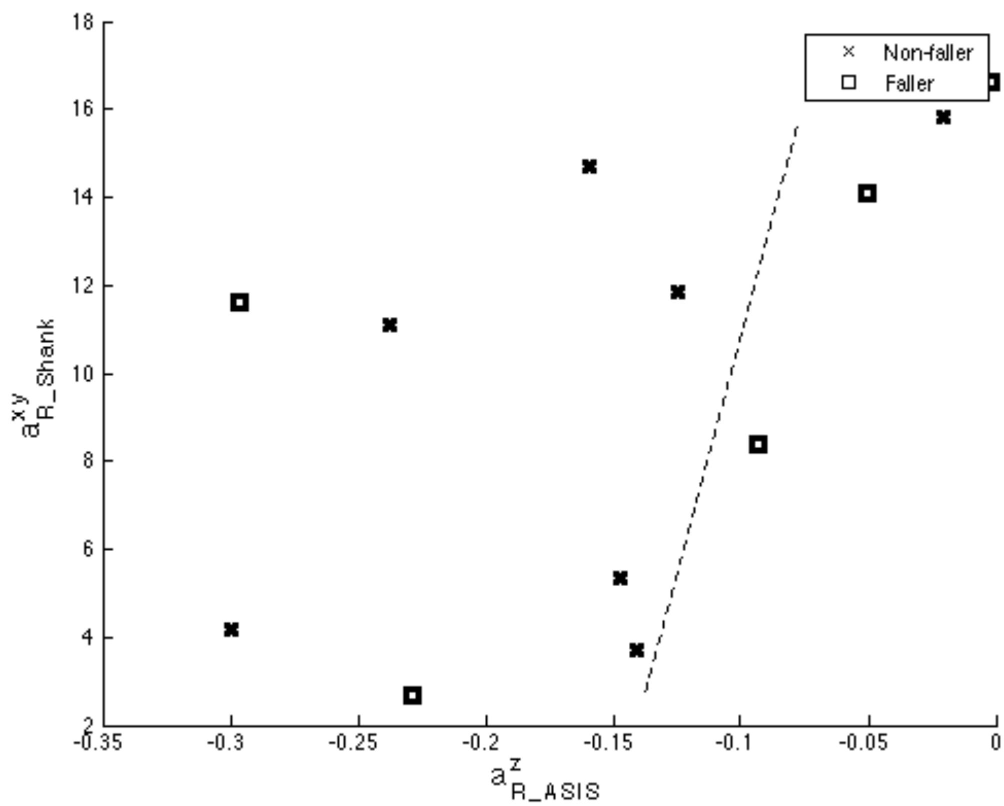


Figure 18: 2-D feature map for young fallers and young non-fallers

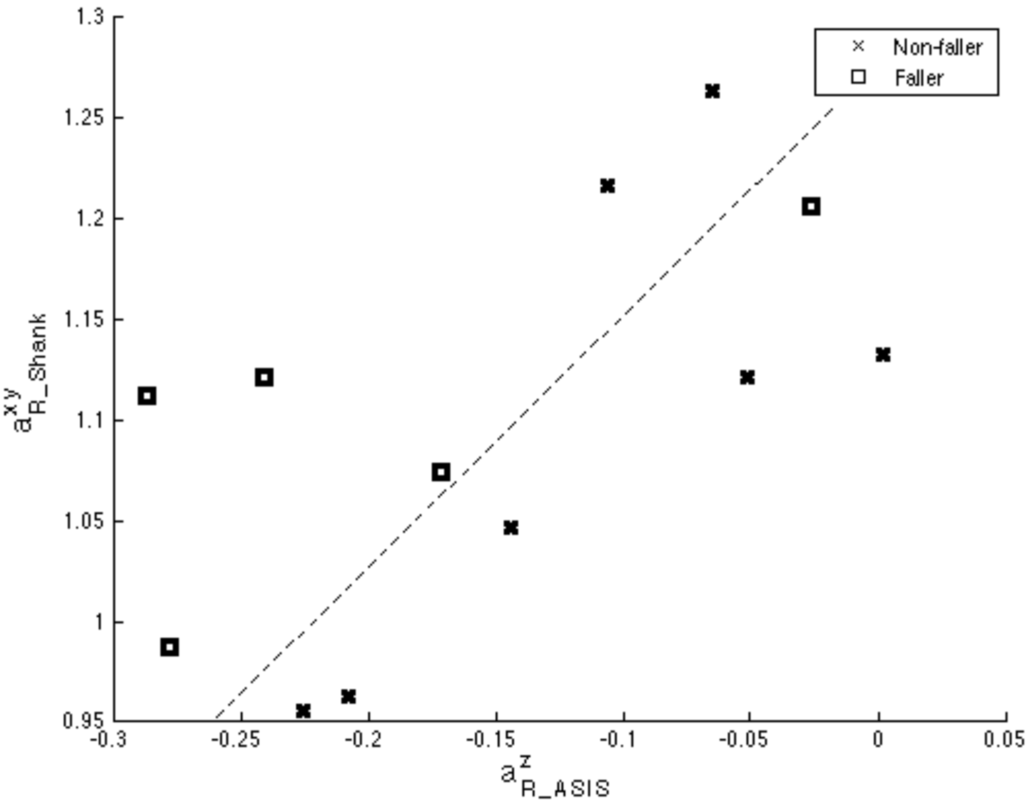


Figure 19: 2-D feature map for older fallers and older non-fallers

As can be seen in Figure 18, young fallers and young non-fallers' features did not show significant separation. As a result, the classifier for differentiating young faller and young non-faller performed poorly. The classifier can be expressed as:

$$-5.2a^{z}_{R-ASIS} + 0.02\omega^{x}_{R-ASIS} - 10.8a^{XY}_{R-Shank} - 0.1\omega^{z}_{R-Shank} + 15.3 = 0$$

Equation 15

Only four out of seven non-fallers and two out of five fallers were classified correctly using the validation data set for the young group. The overall error of this classifier was 50%.

As compared with young group, it appeared more feasible to differentiate fallers and non-fallers in the old age group. The classifier can be expressed as:

$$33.1a^{z}_{R-ASIS} + 0.3\omega^{x}_{R-ASIS} - 6.8a^{XY}_{R-Shank} - 0.2\omega^{z}_{R-Shank} + 14.5 = 0$$

Equation 16

Four out of five non-fallers and five out of seven fallers were classified correctly using the validation data set for the old group. The overall error of this classifier was 25%.

5.4. Discussion

5.4.1. Summary of major findings in this study

The main objective of this study was to investigate if inertial measurement units can measure inertial parameters of pelvic rotation and knee flexion, and therefore be used to differentiate fallers and non-fallers effectively. Results of this study suggested that with two IMUs placed at right ASIS and right shank, acceleration and rotation rate of pelvic rotation and knee flexion could be measured. Such parameters can differentiate fallers and non-fallers within the old group with fairly good accuracy. However, when this method was used to differentiate fallers and non-fallers within the young group, it was not effective. This again confirmed the finding in previous chapters that certain DoG parameters representing gait degradation can be used to assess slip and fall risk for the old population, but they may not be effective measures for the young population because their falls are less related to gait degradation.

Furthermore, this study also found that the IMU method was able to differentiate normal walking condition and constrained walking condition. Given the fact that the constrained walking alters gait significantly, it was not a surprise that the IMU method was sufficiently discriminative when used to differentiate these walking conditions.

5.4.2. On selecting the LDA method for faller and non-faller classification

In general, two completely different approaches can be used for differentiating fallers and non-fallers from IMU measurements of pelvic rotation and knee flexion. One approach is to derive a physical model to explain the relationship between these IMU measurements and the slip and fall risk measures, and use this model to compute slip and fall risk with some explicit equations. Another approach is to bypass the physical modeling, but to build a machine-learning model that is solely based on the knowledge learned from the IMU data itself. In this study, the second approach is taken based on the complexity of the relationship between DoG parameters and the slip and fall risk. Although previous studies analyzed how pelvic rotation and knee flexion could possibly affect slip and fall risk from a biomechanical point of view, still, the relationship was too complex so that no explicit expression can describe the relationship precisely. Since a successful physical model relies on full understanding of every aspects of a system, it was apparently not an appropriate method in this case. A machine-learning method, on the contrary, requires less information about the explicit physical meanings of the model. Therefore, it appeared to be more suitable for the purpose of this study.

More specifically, a common machine-learning method, the linear discriminate analysis (LDA) was used for this study. From a theoretical perspective, the LDA method attempts to find a linear combination of a set of measurements that can be used to predict the class (or category) that one data point should belong to (McLachlan, 2004). Therefore, it fit the purpose of this study (i.e. predicting fallers class or non-fallers class from a set of IMU measurements) very well. From a practical perspective, the LDA method has the advantage of being simple and fast in computation (McLachlan, 2004). Therefore, it can be easily implemented into a standalone IMU solution, or any other portable solutions where algorithm complexity can be a key factor in determining the successfulness of the solution.

5.4.3. Requirements of the LDA method

As suggested by the name of machine learning, the "learning" process is essential to all the machine-learning methods including LDA (Mitchell, 1997). What it implies is that this method requires a certain amount of data to "train" the algorithm and help it "understand" the pattern of the data and the differences between classes that need to be classified. The training data set needs to be representative for the system. Otherwise, the model can be biased. In this study, the representativeness of the training data was ensured by the following two conditions. First, a random trail from each subject / walking condition was selected into the training set. Second, subjects were distributed between low risk group and high risk group with relatively balanced number in each group. Therefore, the selected training data set can be considered representative in the scope of the available data in this study.

The training data set only helps to answer the question of how to combine the existing measurements to build a model for classification. However, the effectiveness (or generalization) of the model needs to be validated by another set of data that is completely different from the training data set (Mitchell, 1997). The generalization determines the usefulness of the model. In this study, generalization was tested by another randomly selected data set that covered each age group and walking conditions.

Another important requirement of the LDA method is that the data presents a Gaussian distribution (McLachlan, 2004). A Chi-square goodness-of-fit test was performed against the IMU measurements used in this study and no significant violation of Gaussian distribution was found.

Lastly, it is important to mention that, the fact that the LDA (or in general, any machine-learning method) requires less information about the physical meaning of the model does not mean that one can arbitrarily select any parameter to feed into the model. Parameters used for classification still need to be relevant to the categories that need to be classified. This study fulfilled this principle by relating the selected IMU measurements to pelvic rotation and knee flexion. With the relationship between these two DoGs and the slip and fall risk that was investigated by previous studies, the IMU measurements were known to be relevant to faller and non-faller classification. Therefore they were considered as valid inputs for the LDA model.

5.4.4. Improving performance of the LDA model

In this study, the overall error of classifying fallers and non-fallers in the old group was 25%. This accuracy level can be considered fairly meaningful given the fact that the method required minimal input from the participants (i.e. only a few walking trails from each participant with a few IMU nodes). However, the classification can be further improved by (a) a better definition of the cost function; or (b) another discriminant model that better represent the clustering of the data. The following paragraphs discussed the possible improvement in detail.

In terms of the cost function of misclassifying one data point, the original model used in this study considered the cost of misclassifying a faller as non-faller the same as the cost of misclassifying a non-faller as a faller. It only served as a proof of concept. However, in practice, the cost function can be different. Usually, the cost of a false alarm and the cost of a miss hit are not the same. For example, if the purpose of a practice is to find out all potential fallers in a community and prevent them from falling as much as possible, the cost of missing a faller (i.e. a miss hit) is higher than the cost of falsely identifying someone as a faller (i.e. a false alarm). However, if the purpose of a practice is to expend limited budget to provide fall interventions only to those who absolutely need help, the cost of falsely identifying someone as a faller will be higher than falsely identifying someone as a non-fallers in this case.

To further illustrate the effect of the cost function on the LDA model, the older subjects' data was revisited. Instead of a universal cost function across faller class and non-faller class, this time it was assumed that the cost of misclassifying someone as a faller was twice as the cost of misclassifying someone as a non-faller. Figure 20 demonstrated how the discriminant model was changed in a 2-D space using the same training data set. The dash line represented the original classification model. It solely attempted at finding out the best linear boundary between fallers and non-fallers. As a comparison, the solid line represented the revisited classification model where the cost of misclassifying someone as a faller was higher. As a result, less non-fallers were actually classified as fallers whereas more fallers were actually classified as non-fallers.

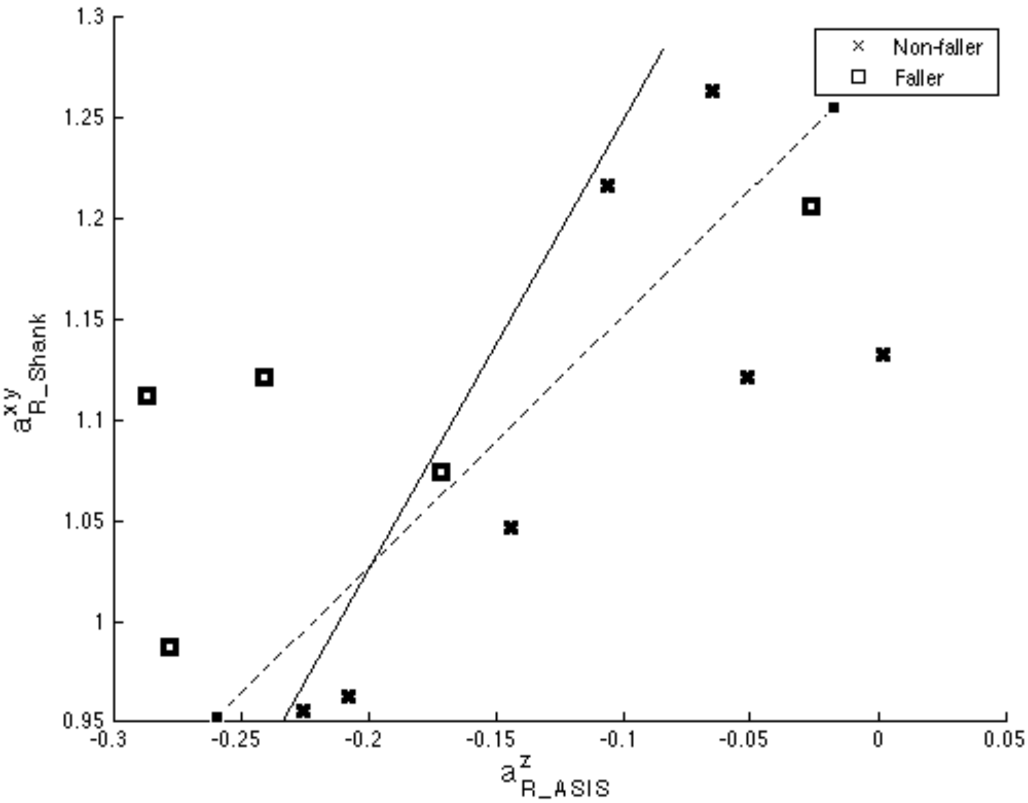


Figure 20: Classification for older fallers and older non-fallers in a 2-D feature map with universal cost function (dashed line) and different cost functions for each class (solid line)

When testing the original classification model against the validation data set, one non-faller was incorrectly classified as non-faller. However, when testing the revisited classification model against the same validation data set, no non-faller was classified as faller any more.

Besides the linear discriminant model, there are other non-linear discriminant models that can be adopted. One example is the quadratic discriminant model that attempts to separate classes with boundaries being a quadratic curve or surface. None of the discriminant model is known to be absolutely superior to other models. The selection of the model is case specific, and may have its own advantages and disadvantages respectively.

5.4.5. Applications of the IMU method in assessing slip and fall risk

Because of the portability of an IMU system, a fall risk assessment method using IMUs has the potential to be applicable for various purposes in different environmental settings. For example, it can be used as a general screening tool among old adults in a nursing facility in order to determine how to distribute fall interventions effectively. It can also be used to track an individual's changes in gait patterns, in order to raise an alarm at an appropriate moment. In a summary, the IMU method has the potential to substitute the traditional motion study equipment when the latter is sometimes overburdening for fall risk assessment in practice.

5.4.6. Limitation of current study

One limitation of the current study was the small sample size. When the number of subjects was used to investigate group difference between fallers and non-fallers, it was sufficient to reveal significant group difference. However, when the number of subjects was used to derive an LDA model for predicting fallers and non-fallers, it can only serve as a proof of concept. In reality, a much larger amount of data needs to be collected in order to establish a reliable model to be used. The training and validation of this larger-scale model can follow the same process as illustrated in this study.

Another limitation of this study was that only time domain features of the IMU signals were fed into the LDA model. The frequency domain features, however, were not included in the current study. Since the frequency domain features can also provide valuable insight into the understanding of gait patterns (Nyan et al., 2006) , future studies may investigate on an improved discriminant model that incorporates frequency domain features as well. Such a model may have better predictability in terms of classifying fallers and non-fallers, as well as providing richer information for diagnosing.

6. CONCLUSION

This study investigated the relationship between determinants of gait parameters and the slip and fall risk. It was found that reduction of the pelvic rotation angle and the knee flexion angle at heel contact, caused either by intrinsic gait degradation or extrinsic gait constraints, resulted in higher slip initiation risk and more occurrences of falls in a controlled environment. This finding expanded our knowledge about how determinants of gait and slip initiation severity are related, and has an important implication to future research in terms of exploring the complex relationship between one's gait profiles and his or her slip and fall risk. This result could also be used to design slip and fall risk assessment tools. Compared with existing fall risk assessment tools, a fall risk assessment tool based on determinants of gait parameters has the potential to reveal the effects of gait abnormities on fall risk more deeply, and provide rich diagnostic information in terms of locations and severity of gait abnormities. Such diagnostic information can be further utilized to guide the design and distribution of fall interventions, in order to maximize the effectiveness and efficiency of various fall interventions.

Furthermore, this study investigated the feasibility of using inertial measurement units for measuring DoGs and assessing slip and fall risk. Results in this study have suggested that it is possible to use two inertial measurement units to measure determinants of gait, and effectively classify fall risk between individuals and across different walking conditions. In modern society, the use of IMU sensors has become an emerging approach for conducting health and fitness evaluations because of their low cost, superior portability, and prevalent existence in consumer electronic devices. From this perspective, this study demonstrated the possibility of developing fall risk screening or monitoring tools on various wireless platforms. The methodology and algorithm used in this study can be easily adapted to future research and applications that have similar objectives.

Finally, it is well acknowledged that numerous factors contribute to one's fall risk. The complex nature of the fall problem determines that no single fall risk assessment tool can fully explain one's fall risk and absolutely overwhelm other methods. As a matter of fact, each fall risk assessment may only provide one dimension of diagnostic information. It is the combination of many effective fall risk assessments that could better depict an individual's overall fall risk, or in other words, draw a more complete fall risk map of an individual. Therefore, the significance of this study can be concluded as adding one more dimension to the existing fall risk assessments. It encourages future research to continue working on expanding the dimensions of the fall risk map, and will potentially lead to a well-accepted paradigm for assessing fall risk, that has both significance in theory and wide applications in practice.

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