Experimental studies and model development for individual-specific fall detection

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**EXPERIMENTAL STUDIES AND MODEL DEVELOPMENT FOR
INDIVIDUAL-SPECIFIC FALL DETECTION**

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ABSTRACT

Falls are a major cause of injuries and fatalities in daily activities and occupational settings. Fall detection has been suggested to be an effective fall prevention strategy. It can help initiate timely medical assistance for fall victims, and/or activate on-demand fall prevention systems (e.g. inflatable hip protectors) to prevent the physical injuries caused by fall impacts. The objective of this research was to develop a novel fall detection model based on the statistical process control chart. Given that a substantial proportion of falls result from slips, this research focused on detecting slip-induced falls. In order to achieve the research objective, three studies were conducted.

The first study determined the appropriate fall indicators for fall detection research by experimentally examining a comprehensive set of kinematic measures. The body kinematic measures were compared between slip-induced falls and non-fall activities (i.e. normal walking and successful recovery after slips). Five kinematic measures were identified as the appropriate fall indicators since they were able to effectively and efficiently differentiate falls from non-fall activities, especially at the early stage of loss-of-balance due to slips.

In the second study, a novel pre-impact fall detection model based on the statistical process control chart was developed and evaluated. The fall indicators were selected based on the experimental findings from the first study. The proposed fall detection model was individual-specific, since it was constructed using the individual historical movement data. The fall detection model demonstrated a high accuracy with sensitivity and specificity up to 94.7% and 99.2%, respectively. In addition, this model can also provide sufficient time for triggering fall protection device in the pre-impact phase, thus being potentially effective in preventing fall injuries.

In the third study, a novel fall indicator defined by a linear combination of multiple kinematic measures was used in the proposed fall detection model. To specify the fall indicator, an optimization procedure was performed in which the trial and error method was used to determine the relative weightings of selected kinematic measures that were associated with the optimal fall detection performance. The sensitivity, specificity, and sum of squared errors of the fall detection model were 97.3%, 99.2% and 0.00133, respectively. The results were superior to those obtained when using fall indicators defined by a single kinematic measure.

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Chapter 1 Introduction

1.1 Background

Falls are a major cause of injuries and fatalities in daily activities and occupational settings. Each year, falls lead to more than two million hip fractures in the US (Hayes et al., 1996). Due to the aging population, researchers projected that this number could reach over six million by the year of 2050 (Cooper et al., 1992). Besides hip fracture, falls are often associated with head injuries and upper extremity injuries as well (Scallan et al., 2004; Hsiao and Robinovitch, 1998). In Singapore, falls and fall related incidents accounts for 85.3% of all injuries in hospital emergency departments (Yeo et al., 2009) and 15%-30% of workplace injuries (Chi et al., 2005; Haslam et al., 2005; Ling et al., 2009). Additionally, over 30% of workplace fatalities and 40% of disabled injuries were related to falls in Singapore (Singapore Ministry of Man Power, 2013).

Falls result in tremendous economic burden onto both the patients and the whole social welfare system (Burge et al., 2007). The direct medical cost for fall-related injuries was \$19.2 billion dollars annually in the US (Stevens et al., 2006). Besides the medical expenditures, an annual cost of \$2.5 billion had to be spent on nursing home care for fall victims in the US (Holbrook et al., 1998).

Slips are one of the leading causes of accidental falls. About 25% of falls were caused by slips (Lloyd and Stevenson, 1992). In workplace, 43% of same-level fatal falls were triggered by slips (Courtney et al., 2001). Besides, slip recovery efforts could contribute to high rates of overexertion injuries (Courtney et al., 2001). Therefore, slips and falls

have attracted much attention recently. Prevention of injuries related to slips and falls has already been an imperative health concern.

1.2 Motivation

Due to the high frequency and high severity of fall accidents, prevention of falls has been well recognized as an important research topic. In general, fall prevention strategies can be classified into two groups: proactive and reactive. Proactive fall prevention aims to prevent the occurrence of falls, while reactive fall prevention aims to reduce the impact and consequences of fall-related incidents.

In order to proactively prevent fall accidents, risk factors that potentially contribute to falls must be identified and modified. However, falls are multi-factorial. It is almost impossible to explore all risk factors of fall accidents. Meanwhile, certain risk factors, such as age-related physiology changes, can hardly be modified by any preventive strategies. Thus, proactive fall prevention strategies are far from effective. Reactive fall prevention strategies appear to be able to overcome the limitations of proactive strategies. However, traditional reactive fall prevention approaches, such as personal protective equipment, are often associated with very low user compliance.

Fall detection belongs to reactive fall prevention that can protect fallers by minimizing injury severity (Bourke et al., 2007). In particular, fall detection is effective in controlling fall hazards mainly from two aspects: initiating timely medical assistance for fallers and activating fall prevention device (e.g. inflatable airbag) to avoid physical impacts (Shi et al., 2006; Tamura et al., 2009). Gurley et al. (1993) reported a significant reduction in mortality rate if early detection and treatment was provided after falls among

older people. Rajendran et al. (2008) suggested that fall detection followed by immediate reporting to caregivers can improve health outcome by initiating faster and appropriate medical care. Tamura et al. (2009) developed a wearable airbag that can be triggered by a fall detection system. The airbag can reduce the fall impact thus minimizing the fall injury.

Though fall detection has been suggested to be an effective fall prevention strategy, research in this aspect is far from enough, given several common limitations in the existing fall detection research. First, the development of existing fall detection models lacks experimental basis. Specifically, fall indicators and fall detection parameters (e.g. detection threshold) were always arbitrarily specified (Wu and Xue, 2008; Sullivan et al., 2009). Second, fall detection parameters were always set at the same values for different individuals (Bourke et al., 2008c; Nyan et al., 2008a; Nyan et al., 2008b). In other words, existing fall detection models cannot address individual differences adequately. Third, previous fall detection models were mainly used to detect voluntary falls (Nyan et al., 2008a; Nyan et al., 2008b). However, most falls in real life are involuntary. Furthermore, fall-like activities (e.g. recovery from external perturbations) were not taken into account when developing and evaluating existing fall detection models. Due to these limitations, the existing fall detection models may not be effective in real-life applications. This research was designed to address the above mentioned limitations in the existing fall detection research.

1.3 Research objectives

The overall objective of this research was to develop a novel fall detection model that can well address the limitations in the existing fall detection research. In order to achieve this objective, three studies were carried out. In Study One (Chapter 3), effort was made to determine the appropriate fall indicators for fall detection by experimentally examining a comprehensive set of kinematic measures. In Study Two (Chapter 4), by using the fall indicators identified from Study One, a novel individual-specific fall detection model based on the statistical process control chart was developed and evaluated. Study Three (Chapter 5) aimed to examine whether the fall indicator defined by a linear combination of kinematic measures could lead to better fall detection performance than those defined by a single kinematic measure.

Chapter 2 Literature Review

2.1 Falls and their consequences

Falls remained one of the leading causes of fatal and nonfatal injuries worldwide (Antao et al., 2008; Aschan et al., 2009; Bakhtiyari et al., 2012; Zytoon, 2012). In the year of 2002, over 12,900 adults in the US died as a result of falls, and over 1,016,700 patients were treated in emergency departments for fall related injuries, 388,000 of whom were subsequently hospitalized (Stevens et al., 2006). In Singapore, falls and fall related incidents represented 85.3% of all injuries in hospital emergency departments (Yeo et al., 2009). Falls were the leading cause of death from injury for people over the age of 65 (Province et al., 1995). Seventy percent of all emergency department visits by people over the age of 75 were related to falls, and over 40% of hospital admissions in this age group was resulted from fall-related injuries (Sattin, 1992).

In the workplace, falls accounted for 15%-30% of occupational injuries (Chi et al., 2005; Haslam et al., 2005; Ling et al., 2009). Approximately 15% to 40% of accidental deaths in the workplace were caused by falls in different countries (Kang, 2010; Singapore Ministry of Manpower, 2013; Toyosawa and Katsutoshi, 2010; US Bureau of Labor Statistics, 2012). In the US, more than 24% of non-fatal injuries in the workplace were associated with falls (US Bureau of Labor Statistics, 2010). Falls were also reported as the leading cause of injuries in construction, food service industry, mail delivery and healthcare sector (Bentley 1998; Bell et al., 2008; Chang et al., 2008; Drebit et al., 2010; Gauchard et al., 2001; Hsiao and Simeonov, 2001). For example, falls accounted for

approximately one third of occupational injuries in construction work in the US (Rivara and Thompson, 2000).

Falls can cause adverse physical and psychological consequences and huge economic burdens. This was getting more imperative with the aging population. The most commonly seen injury associated with falls was hip fracture. Approximately one fourth of fall accidents lead to hip fracture (Lauritzen et al., 1993). Each year, more than two million hip fractures injuries in the US were attributable to falls (Hayes et al., 1996). Besides, falls were the leading cause of head injuries (Scallan et al., 2004). Falls also commonly lead to upper extremity injuries such as arm and wrist fractures which were likely due to the use of the upper extremities as a fall-arrest strategy (Hsiao and Robinovitch, 1998).

Falls can result in adverse psychological consequences such as fear of falls, anxiety and depression (Berry and Miller 2008; Boyd and Stevens, 2009; Brown, 1999; Hellstrom et al., 2009; Tinetti et al., 1994). Fear of falls was common among elderly fallers. About one third of the elderly developed a fear of falls after a fall accident (Vellas et al., 1997). Fear of falls can cause impaired mobility and decreased functional status (Vellas et al., 1997). As a consequence, fall victims may lose self-confidence to engage in normal daily activities. Eventually, this can result in various post-fall health problems including dependence, loss of autonomy and social withdraw (Tinetti et al., 1994; Martin et al., 2005).

Falls were associated with tremendous economic burden to both patients and whole social welfare system. The direct medical costs totaled \$0.2 billion dollars for fatal and \$19 billion dollars for non-fatal fall related injuries in the US (Stevens et al., 2006). The

cost of occupational fall-related injuries in the US was more than \$13 billion annually (Liberty Mutual Research Institute for Safety, 2012). The average cost of one fall injury episode for people above 65 year old in Finland and Australia was \$3611 and \$ 1049, respectively (Hendrie et al., 2003; Nurmi and Luthje, 2001). Besides the medical expenditures, an annual cost of \$2.5 billion had to be spent on nursing home care for all fall related injuries in the US (Holbrook et al., 1998). Evidence showed that the cost burden associated with fall injuries grew by approximately 35% from 1998 to 2007, more than any other injury category (Noy, 2010).

2.2 Risk factors of falls

Fall accidents occurred as a result of a complex interaction of risk factors. Understanding fall-related risk factors was an essential component for fall prevention programs. According to the World Health Organization (2007), the fall-related risk factors can be categorized into four dimensions: biological, behavioral, environmental and socioeconomic factors.

2.2.1 Biological risk factors

Biological risk factors included the change of individual characteristics that were pertaining to the human body (World Health Organization 2007). For instance, physiological changes associated with aging, such as the decline of physical, cognitive, and sensory capacities shall increase the fall risk (Lord et al., 2001; Maki 1997; Prince et al., 1997).

Maki et al. (1994) compared the postural responses to unpredictable postural perturbations between healthy elderly and young adults. They found that the elderly were twice as likely to take additional steps to regain stability as young adults. They suggested that this age-related decline of the ability to regain balance may increase the fall risk among elderly. Shigematsu and Okura (2006) pointed out that older adults had impaired balance recovery skills due to the declining ability of rapidly and efficiently contracting the muscles of the lower extremities. Besides the decreased muscle strength, elderly have diminished input from the visual, proprioceptive, and vestibular systems which may compromise the balance skills and increase the probability of falls.

Disease or illness was another important biological risk factors associated with falls. Morbidities such as Parkinson's disease, osteoarthritis, visual impairment and dementia were the leading causes of falls among elderly (Nevitt and Cummings, 1994). Falls were the major complication in stroke rehabilitation. Studies revealed that 23-39% of stroke patients suffered reoccurrence of falls (Batchelor et al., 2010; Jørgensene et al., 2002; Nyberg et al., 1995; Simpson et al, 2011). Visual spatial problems, impairment in balance, and residual dizziness were all strongly associated with recurrent falls among stroke patients (Nevitt et al., 1994). Lawlor et al. (2003) investigated the effect of chronic diseases and drug use on fall risks in elderly women. They found that circulatory disease, chronic obstructive pulmonary disease, depression and arthritis were all associated with an up to 32.2% increased fall risk. Two classes of drugs, i.e. hypnotics and anxiolytics, and antidepressants were found to be associated with a 50% increased of fall risk for each class.

2.2.2 Behavioral risk factors

Behavioral risk factors were related with risk-taking behaviors such as climbing, reaching and bending while performing the activities of daily living (ADLs), also including life-style factors such as choice of cloth and shoes, alcohol use, poor diet and lack of exercise. Clemson et al. (1996) found that most elderly women had their own behavioral strategies to minimize fall risk in ADLs, such as “moving slowly” and “care in environment”. However, there was an increased fall risk when these “behavioral controls” were not consistently applied. Gallagher et al. (1996) found that many elderly fell as a result of carrying an object such as handbag or grocery bag.

Lack of physical activities can inadvertently cause further atrophy of muscle around an unstable joint due to disuse, thus increasing the fall risk (Skelton, 2001). Gregg et al. (2000) found that sedentary individuals were associated with a 20-40% increase of fall injury risk compared with people who were active in physical activity. Evidence showed that lack of physical activities could further increase the risk of falls and injuries through the functional capability decline (Yardley et al., 2008). However, it was difficult to demonstrate whether the lack of physical activities alone was a unique fall-related risk factor, because lack of physical activities was highly associated with biological changes such as muscle function decline (Skelton, 2001). Thus the effect could be confounded.

Choice of footwear could be another behavioral fall-related risk factor. Two studies revealed that slippers had the highest frequency of being worn at the time of a fall, mostly attributed to the fact that slippers were lack of heel support (Sherrington and Menz, 2003). Sherrington and Menz (2003) found that shoes with no fixation were more likely to be associated with high fall risks. Recently, Menant et al. (2009) have recommended

that both young and older people should wear “well-fitted shoe with a firm fastening mechanism, a medium sole hardness, a low square heel, a high collar and no flare” to reduce fall risk. Other risk behavior included stairs negotiation for elderly (Kim, 2009; Wright and Roys, 2008) and some occupational settings (Bentley et al., 2005).

2.2.3 Environmental risk factors

Most falls were deemed to be the result of an interaction between individual characteristics that increase an individual's propensity to fall and environmental hazards (Tinetti et al., 1994). Typical environmental hazards that may result in falls include slippery surfaces, narrow steps of stairs, and insufficient lighting (Tinetti et al., 1994). Approximately 50% of falls among community dwelling elderly were due to environmental causes (Feder et al., 2000). The environment risk factors also account for the high fall rate found in hospitals and nursing homes (Oliver et al., 2000). Hignett and Masud (2006) suggested the wheeled furniture and unfamiliar environment, combined with the biological risk factors of the patient (e.g. acute illness, medication) may lead to the high fall rate.

Most homes contain potential hazards, and many people, especially elderly, fell due to accidents inside the home or immediate home surroundings (Lord et al., 2001; Van Bommel et al., 2005). Clemson et al. (1996) conducted a case control study to compare the prevalence of in-house environmental hazards between old people with and without recurrent falls or a recent hip fracture. They found that several specific environmental hazards were associated with increased risk of recurrent falls or hip fracture including hazardous toilet railings, doormats and in-house steps, etc. They further reviewed the literature regarding environmental hazards and demonstrated a range of specific

environmental factors that contributed to high fall risks. These factors included in-house stairways, obstacles in traffic ways, flooring, etc. (Clemson et al., 1996). Isberner et al. (1998) reported that the absence of handrails and the presence of uneven floors were more commonly found in the former. Similarly, Fletcher and Hirdes (2002) found that those who had one or more environmental hazards in their homes were more likely to experience falls. Lord et al. (2003) suggested that this fact may be due to that vigorous elderly were more likely to take part in risk-taking behaviors. Among all the environmental risk factors associated with falls, slippery surface was one of the leading causes of accidental falls (Stevens et al., 2006). A specific review of slip-induced falls and the corresponding gait dynamics was given in Section 2.3.

2.2.4 Socioeconomic risk factors

Socioeconomic fall-related risk factors were introduced by World Health Organization (WHO) (2007) as one of the key components of the fall risk model for older people (World Health Organization, 2007). According to WHO, socioeconomic fall-related risk factors were “those influencing social conditions and economic status of individuals as well as the capacity of the community to challenge them”. These factors included: low income, low education, inadequate housing, lack of social interaction, limited access to health and social care (especially in remote areas), and lack of community resource (World Health Organization, 2007).”

Reyes-Ortiz et al. (2004) conducted a two-year cohort study to estimate the prevalence of falls and the risk factors associated with falls in Mexican-American aged 72 and older. They found that old women with unreliable and insufficient incomes, living

alone or in rural areas, faced an increased fall risk. Lower income, often resulting in poor environment and diet and inability to access the health care services was accountable for the increased fall risk. Although socioeconomic fall-related risk factors were particularly evident in rural areas and developing countries, they have not been studied scientifically. The need of related studies is imperative.

2.2.5 Summary of fall-related risk factors

Table 2.1 summarizes the above mentioned fall-related risk factors. Although the risk factors can be categorized from different aspects, falls were often triggered as a result of a complex interaction of several risk factors. For example, the interaction of biological factors (e.g. age) with environmental risks (e.g. slippery floor) can increase the risk of fall. Lockhart et al. (2003) suggested that the reason for the elderly to have a higher fall risk was the decrease of muscle strength, which lead to a higher level of frailty and intensified the risk of fall due to some environmental hazards. Another example of interactive effect of multiple fall-related risk factors was the “long-lie” problem after falls. “Long-lie” referred to the situation when people remained on the ground for more than one hour after falls. “Long-lie” was associated with high mortality rate among elderly (Lord et al., 2001; Wild et al., 1981). “Long-lie” resulted from the increased biological risk factor of weakness or illness among elderly, who had insufficient strength to get up after falls and the isolation of elderly, which was an often neglected socioeconomic risk factor. Many fall prevention approaches were developed in order to reduce the fall risks by considering those fall-related risk factors. Those fall prevention approaches were reviewed in Section 2.4.

Table 2.1 Risk factors of falls

1) Biological risk factors Age and Aging effect (e.g. physical and cognitive capacities decline) Disease or illness (e.g. Parkinson's disease, osteoarthritis, visual impairment and dementia, post-stroke)	2) Behavioral risk factors High risk occupation (e.g. construction, mail delivery) Climbing up/down stairs (for frail elderly) Lack of physical activities Intake medications, excess alcohol use
3) Environmental risk factors Slippery floors Narrow steps of stairs Home hazard (poor designed furniture, wet-floor bathroom) Insufficient lighting	4) Socioeconomic risk factors Lack of awareness of fall danger Limited access to health and social care especially Lack sufficient knowledge for care giver Lack of social interaction Low income, low education, inadequate housing Lack of community resources

2.3 Slips and falls

Slips were the leading cause of involuntary falls. Approximately 25% of all falls were caused by slips (Lloyd et al., 1992). It was also reported that 64% of work-related falls and 43% of occupational same-level fatal falls were triggered by slips (Courtney et al., 2001). Slip-induced falls often led to grave consequences such as hip fracture, head trauma or even death (Mathers et al., 1998; Stevens et al., 2008; Thomas et al., 2008). In addition to the risk of fall-related injuries and fatalities, slip recovery efforts could contribute to high rates of overexertion injuries (Courtney et al., 2001). Therefore, it is

important to understand the causes, biomechanics and fall resisting body dynamics related to slip incidence. This knowledge can be used for developing effective risk assessment tools and interventions for reducing fall incidents (Yang et al., 2009).

The biomechanics of slips were extensively studied. Ground Reaction Force (GRF) at the shoe-floor interface was considered as the most critical biomechanical factor in slips (Redfern and Bidanda, 1994). Cham and Redfern (2002b) identified general characteristics of GRF profile during slip trials under laboratory settings. They pointed out that both peak shear and normal GRFs were significantly reduced during slips events. Besides, the transfer of body weight to the supporting leg did not seem to be completed in slip trials. Similarly, Cham and Redfern (2001) used GRF data to study the lower extremity corrective reactions during slips. They reported a 25-45% reduction in shear forces after a slip compared with normal gait and suggested that such changes should be associated with corrective response or the attempt to bring the foot back near to the body.

The required coefficient of friction (RCOF), defined as the minimum coefficient of friction (COF) needed to support human locomotion, was the biomechanical variable most closely associated with the measured frictional properties of the shoe-floor interface (Redfern et al., 2001). It represented the general friction demand or the minimum coefficient of friction that must be available at the shoe-floor interface to prevent initiation of forward slips (Redfern et al., 2001). RCOF was used to identify when the slip initiation would occur during gait cycle. Lockhart et al. (2003) used RCOF to represent initial friction demand in slip and falls. Redfern et al. (2001) suggested that initiation of a slip occurred whenever the frictional force opposing the movement of the foot was less

than the available horizontal shear force acted on the foot during the heel contact phase of the gait cycle.

Despite the wide use of the RCOF, the RCOF extraction method was not standardized (Chang et al., 2011). Recently, Chang et al. (2012) attempted to standardize the methodology to extract the RCOF. They amended the calculation method of RCOF by adding the transverse shear component of the GRF. They found that RCOF actually increased if the transverse component was taken into account. The amended RCOF could occur much earlier than the RCOF without adding transverse shear component. Therefore, the available response time for the human to take reactive actions during a slip incident might be shorter than previously expected.

As indicated by many studies, kinematic parameters such as heel contact velocity and walking speed can affect GRF by alternating the magnitude of shear force at the shoe-floor interface (Winter, 1979; Prince et al., 1997; Lockhart et al., 2003). It was reported that increased walking velocity and step length would cause increased friction demand (Myung et al., 1997). Based on these findings, slower walking speeds and shorter step lengths observed in older adults appeared to be able to lower friction demand, thus resulting in a decreased likelihood of slips and falls. However, some studies reported conflicting results (Gehlsen et al., 1990; Feltner et al., 1994). For example, Bhatt et al. (2005) found that gait with slower walking speed was more unstable compared to fast speed because slower speed could lead to more posterior center of mass (COM) position with respect to the leading foot at touchdown.

Body dynamics during slips were of great interest when studying slips and falls (Cham et al., 2002a). Knowledge on body dynamics can facilitate better understanding of

the recovery attempts upon slips which was very useful for developing fall prevention strategies (Moyer et al., 2006). Redfern et al. (2001) suggested that body dynamics during balance recovery after slips were affected by various types of factors, such as anthropometrical factors, (e.g. foot geometry, body mass and its distribution, or segment length and height), physiological factors (e.g. strength, rate of muscle force rise, or gains and delays of feedback control), cognitive factors (e.g. dual task during slips), and behavioral factors (e.g. balance recovery attempt).

Slip prevention strategy can be initiated prior to, during, or after the loss of balance due to slips (Patla and Edelstein, 1992; Woollacott and Tang, 1997). A good example of proactive slip prevention strategy was observed as significant reduction in the peak RCOF recorded during walking trials when the participants anticipated the possibility of slips (Cham et al., 2002b). The perception of the danger of slips affected the joint moments and the loading rate on the supporting foot prior to the slip initiation.

As most slip and fall incidences occurred unexpectedly, the reactive balance recovery was more often applied during slips. The slip recovery attempt involved musculoskeletal coordinate, neuromuscular control, and their interaction with the environment (Redfern et al., 2001). A wide range of reactive recovery strategy was studied (Parijat and Lockhart, 2008; Troy et al., 2009). Among those responses, compensatory stepping was the irreplaceable important recovery strategy, especially in response to a large disturbance (Bhatt et al., 2005). Pavol et al. (2004) identified the relationship between falls and the magnitude of stepping response. A diminished stepping response including a collapse of the support limb or a shortened protective step can easily lead to fall. The support limb collapse resulted in a large, rapid hip descent and shortened

recovery step. Therefore, the recovery limb could not arrest the descent of the hip and people would fall before completing any additional steps.

Kinetic measurements such as joint moments or forces of lower extremity were also well studied during slips and falls. The changes of joint moments upon slips represented the biomechanical reactions of human body to maintain or recover balance. The balance recovery after slips was sometimes achieved by using an unexpected and unrehearsed stepping strategy which resulted in larger moment deviations from the steady gait pattern (Carty et al., 2011). Cham et al. (2002a) reported increased extension moment at the hip and increased flexion moment at the knee upon slip initiation. These moment changes were responsible for corrective reactions attempted to recover balance from slips.

The age-related differences in biomechanics of slips were also studied. Lockhart et al. (2003) conducted an experiment with two age groups (young and old) walking on slippery and non-slippery surfaces. They calculated kinetic and kinematic measures and the results indicated that despite the much slower walking speed, older people had a significantly faster horizontal heel contact velocity at slip initiation compared with younger participants. Therefore, older participants slipped longer and faster than younger participants. Their findings suggested that age-related gait changes had a significant effect on the initiation of slip-induced falls. Lockhart and Kim (2006) conducted an experiment to determine whether a decreased hamstring activation rate among the elderly was responsible for a higher heel contact velocity and increased likelihood of slip-induced falls. Two age groups, 14 young and 14 old adults were involved. Their results

suggested that heel contact velocity in younger adults was sufficiently reduced before the heel contact phase due to the high hamstring activation rate.

2.4 Fall prevention strategy

Fall prevention was essential in planning of effective injury prevention among fall prone populations (Kannus et al., 2005; Stokes, 2009). In general, fall prevention approaches can be classified as proactive prevention and reactive prevention (Figure 2-1). Proactive fall prevention aimed to prevent the occurrence of future falls by modifying risk factors. It can be achieved mostly through fall risk assessment, strength and balance training, environmental modifications, and behavioral change advice program, etc. (Kannus et al., 2005). On the other hand, reactive fall prevention aimed to reduce the fall impact and fall-related injuries upon the occurrence of fall accident. One common practical method was providing personal protective equipment (PPE) such as hip pad. Another important method was personal emergency response system (PERS) which was often used by elderly. The existing research regarding to fall prevention strategies were reviewed according to their categories shown in Figure 2-1, followed by a summary of their objectives and limitations.

Figure 2-1 Outline of fall prevention approaches

2.4.1 Proactive fall prevention

2.4.1.1 Fall risk assessment

Fall risk assessment was used to identify the people at high fall risk, thus maximizing the effectiveness of any proposed fall prevention intervention (Rubenstein, 2006). For example, Najafi et al. (2002) found that the postural transition duration was significantly higher for the high fall-risk group compared with the low fall-risk group. They further revealed that postural transition duration can be the objective criterion for fall risk assessment. Oliver et al. (2004) found that “falls history” and “prescription of

‘culprit’ drugs” were the consistently emerged falls risk predictors, by which fall risk can be predicted with sensitivity and specificity in excess of 70%. Greene et al. (2010) identified 29 parameters (e.g. walk time, number of gait cycles, mean angular velocity, etc.) that were significantly discriminated between patients with fall history and those without fall history. They reported 77.3% sensitivity and 75.9% specificity for fall prediction with those parameters.

2.4.1.2 Strength training

Physical frailty such as declined abilities in muscle strength, motor coordination, and sensory organization were the major biological factors leading to concurrent falls in fall prone populations (Paw et al., 2008). Consistent evidence had shown that strength and balance training were useful interventions for preventing falls (Lundebjerg et al., 2001; Paw et al., 2008; Persch et al., 2009). These programs were usually performed twice or three times per week and normally lasted for 45-60 minutes per session (Barry and Carson, 2004; Hunter et al., 2004; Inaba et al., 2008). It was reported that a reduction of 15-50% of fall incidents can be achieved after strength and balance training (Kannus et al., 2005).

There have been numerous training or exercise schemes proposed to help prevent falls in older adults. A majority of the programs were facility-based group exercise programs, which aimed to improve physiological conditions associated with fall risks in the frail elderly such as declined muscle strength (Carter et al., 2001a; Carter et al., 2001b; Cumming, 2002), inflexibility (Marigold et al., 2005), and decline in coordination, proprioception and reaction time (Barnett et al., 2003).

The strength training usually focused on improving the lower extremity muscular strength by using simple equipment such as elastic resistance bands (therabands) and soft weights (Binder et al., 2002). For example, Hess and Woollacott (2005) developed and evaluated a ten-week high-intensity lower extremity muscle strength training program. Their results revealed that strength training could safely and effectively strengthen lower extremity muscles among balance-impaired older adults, thus aid in preventing potential falls. Pijnappels et al. (2008) conducted a 16-week resistance training in which knee extension and leg press exercises were carried out once per week. They found that people had a higher maximum force generating capacity during balance recovery from trips after the training. Kawagoe et al. (2010) investigated the effects of limbering up exercises on fall prevention for elderly workers. They found that the static balance, agility, flexibility and muscle strength in elderly workers were significant improved through this program, and the fall risks were significantly decreased at the end of the eight months period.

2.4.1.3 Balance training

The balance training involved exercises that challenge balance such as a perturbed walking exercise. Research revealed that balance training was associated with a 60% reduction of fracture risk in elderly women (Korpelainen et al., 2006). For example, Lord et al. (2003) developed a group exercise involving challenging-balance tasks such as lifting toes and heels, rotating task and lateral movement. They revealed a positive effect on preventing falls and maintaining physical function among frail older people. Barnett et al. (2003) introduced a balance training program including modified stepping practice, change of direction, dance steps practice combined with using resistance bands for both

the upper and lower limbs. Their results indicated that participation in this weekly training could improve balance and reduce the rate of fall. Shimada et al. (2004) conducted an unexpected perturbation gait exercise by changing the speed of a bilateral separated treadmill. They compared the balance training group with a control group who just performed normal exercises. The balance training group showed significant improvement in balance and reaction time compared with the control group.

2.4.1.4 Balance training by Tai Chi exercise

Among balance training programs, Tai Chi exercise was widely accepted as an effective and efficient way of maintaining musculoskeletal health and reducing the propensity of fall (Li et al., 2001). It was clearly confirmed that Tai Chi could improve the body balance for elderly people. For example, Li and Fisher (2005) analyzed the effect of Tai Chi on fall risk reduction by evaluating the outcome through Berg Balance Scale, Dynamic Gait Index, Functional Reach, and single-leg standing assessment. Tai Chi participants showed improvements in functional balance and a significantly reduction on the fall risk. Wolf et al. (2003) examined the occurrence of falls in three groups of older participants: the Tai Chi group, the regular-balance-training group, and a no-training group. Those who participated in Tai Chi saw a 47.5% reduction in the risk of falls, whereas the others did not experience a significant reduction. Tsang and Hui-Chan (2003) found that Tai Chi practitioners initiated voluntary weight shifting in the limits of the stability test more quickly than control groups. Moreover, they could lean further without losing stability and showed better control of their leaning trajectory.

Gatts and Woollacott (2007) found that the Tai Chi practitioners adapted more efficacious controlling stepping strategies of the swing leg during slips. However, there was no comprehensive or quantitative basis for understanding the mechanisms of Tai Chi and why Tai Chi was a better exercise for improving balance and posture control than other traditional balance exercises, and what made it uniquely effective. Further investigation was required (Hong and Li, 2007).

2.4.1.5 Balance training through motor learning

Some fall prevention programs were based on the theory of motor learning. Motor learning refers to the process of improving the motor skills, smoothness and accuracy of movements (Magill, 1998). It can be achieved through practice, training and/or experience which resulted in relatively permanent changes in behaviors (Bhatt and Pai, 2008). Older adults still had the motor and sensory abilities necessary to recover from a large postural perturbation without fall (Owings et al., 2001; Pai et al., 2010). However, integration and coordination of these abilities may decline with ageing and compromised the ability to achieve successful balance recovery (Prince et al., 1997). Training can help elderly to regain this ability.

Numerous studies revealed that people improved the ability to recover from a balance loss upon repeated exposure to a slip-perturbation (Bhatt et al., 2006; Pavol et al., 2002). The exposure to a slip-perturbation may allow older adults to effectively re-learn appropriate sensory integration and muscle coordination, and improve their ability to recover from larger postural perturbations (Maki et al., 1994). Owings et al. (2001) reported that adaptations of stepping responses after repeated exposures to a simulated

balance perturbation could consistently improve trip recovery ability. Similarly, Pavol et al. (2002) demonstrated an improvement of slip recovery after repeated exposures to slip perturbations. Parijat and Lockhart (2012) assessed the efficacy of simulated slip training in improving balance and reducing falls. They found that the slip training group obtained both proactive (e.g. increased whole body center of mass velocity and transitional acceleration prior to slips) and reactive (e.g. quicker muscle onset and peak activation and quicker slip stop response) control strategies from repeated slip trials. They also revealed a 79.3% reduction in injuries for those who received repeated exposures to a slip training compared to those who received traditional training. However, many studies showed that motor training had a short term effect unless keeping up the training (Cochrane et al., 2004). The extent to which the observed learning persisted beyond the experimental session remained unknown.

2.4.1.6 Sensory feedback enhancement

As declined sensory system was known as a biological fall-related risk factor (Lord et al., 2001), many studies focused on enhancing the sensory feedback for fall prevention. Suomi and Kocaja (2001), for example, evaluated the effect of wearing magnetic insoles on balance control. Significant reduction in postural sway was found for the elderly participants wearing the magnetic insoles, indicating a reduction of fall risks. Priplata et al. (2003) demonstrated that vibrating gel-based insoles led to significant reduction in postural sway for both young and old adults. The effect was more significant for older adults whose threshold of tactile sensitivity was higher than that of their younger counterparts.

Perry et al. (2008) found facilitatory insole can improve lateral stability during gait, and less fall incidents were observed for those who wore facilitatory insole compared with those wore conventional insoles. Maki et al. (2008) proposed a footwear insert that was designed to cause an indentation of the skin and thereby stimulate the cutaneous mechanoreceptors located near the periphery of the sole. They found this footwear insert can improve balance stability. Wall et al. (2009) found that vibrotactile feedback of body tilt improved dynamic gait index (DGI) (which was considered as a fall risk indicator) in community dwelling older adults. A wearable device was used to estimate the vertical trunk tilt and feedback this information to the participant. This could provide the older adults with the additional orientation information. A significant improvement of the total DGI score was found while wearing the vest, indicating vibrotactile feedback as an effective fall prevention intervention.

2.4.1.7 Environmental modification

Environmental modification refers to converting or adapting to the environment including removing hazards, adding special features, moving items or furnishings, modifying light or floor, etc. (Pynoos et al., 2010). Research indicated that environmental modification was effective in preventing falls (Day et al., 2002; Pynoos et al., 2010). For instance, Krauss et al. (2008) suggested some hospital environment modification approaches, including placing the commode adjacent to the bed, locating the patient in a bed near to toilet in multi-bed bays, and removing obstacles from the bed-toilet pathway for fall prevention. They demonstrated these approaches could reduce the falls in hospital rate.

In spite of its importance, environmental modification was an under-utilized strategy in fall prevention. Barriers included cursory assessments, difficulty in obtaining funds and a patchwork delivery system that was difficult to access (Pynoos et al., 2010). Development in the field was needed, including better training of agency staff in assessing problems, greater involvement of occupational therapists, and more attractive products such as designed-for-safety furniture (Kinirons and Martin, 2003; Haines et al., 2004).

2.4.2 Reactive fall prevention

2.4.2.1 Personal protective equipment

Reactive fall prevention aimed to provide instant protection upon falls. Personal protective equipment (PPE) was a commonly used reactive prevention strategy. PPE prevented fall-related physical injuries in a direct manner. Typical PPE included hip protectors, knee protector or various other forms of protective devices. Studies showed that PPE was effective in reducing the severity of fall injuries (Kannus and Khan, 2001). The most common type of injuries was hip fracture (Greenspan et al., 1998). Hence, a logical option to prevent fracture would be a specifically designed device to protect the hips. Hip protection aimed to shunt the energy of an impact away from the greater damage to the soft tissues around proximal femur and to absorb part of the energy of an impact (Hayes et al., 1993).

Honkanen et al. (2006) reviewed the hip protector usage in 14 randomized trials. They reported the use of protectors might help reduce the risk of hip fracture. Although research had revealed that fall impact can be acting on other parts of the body such as

arms and knees (Palvanen et al., 2000; Swischuk, 2004), methods to protect bony sites other than the hip were seldom seen (Kannus and Khan, 2001). Wearing protective device such as foam pads, plastic shields usually met with high patient resistance to routine wear, partially because of the added bulk under clothes and the perception of weakness (Van Schoor et al., 2002).

2.4.2.2 Personal emergency response system

Another reactive fall prevention approach was by possessing a personal emergency response system (PERS). The PERS was normally designed as a device with button which can be pressed to contact the emergency center through the phone line or wireless technology (Porter 2005). Redd et al. (1995) reviewed the PERS usage among elderly who lived alone and reported the frequency of PERS usage varied from 0.44 to 0.84 per subscriber per year. PERS can reduce the duration of home attendant services (Redd et al., 1995). Thus it can potentially reduce the fall injury severity. Mann et al. (2005) conducted a survey study on how elderly perceived and used PERS. Six hundred and six participants above 60 years old were involved. They found that PERS could enhance the feeling of security thus had a positive psychological impact on elderly who lived alone. However, they also found that old people tended not to use PERS due to the cost and lack of knowledge of the device, etc. Another study revealed that the usage of PERS was found to be failed in most case due to physical incapability or conscious unwillingness (Fleming and Brayne 2008).

2.4.3 Summary of fall prevention approaches

Table 2.2 summarizes the fall prevention approaches reviewed in the previous sections. Both proactive and reactive fall prevention approach can be effective. However, there were many limitations which indicate that future research is needed. Those limitations were discussed in the following sections.

Table 2.2 Summary of the fall prevention approaches

Fall prevention approach	Objective	Limitations
Fall risk assessment	Identify the people at high fall risk, thus maximizing the effectiveness of any proposed fall prevention intervention	<ul style="list-style-type: none">• of expertise• Staff and resource intensive• Lack Subjective assessment jeopardize the validity
Strength training	Improve lower extremity muscular strength	<ul style="list-style-type: none">• No consensus on the optimal training requirements or programs• Labor intensive• Some programs may actually increase the fall risk• No consensus on the effectiveness• “How does it work” still not clear
Balance training	Enhance balance skills	
Tai Chi exercise		
Training by motor learning theory	Enhance the motor and sensory abilities	<ul style="list-style-type: none">• Short term effectiveness
Enhance sensory feed back	Enhance the sensory abilities	<ul style="list-style-type: none">• No consensus on the effectiveness
Environmental modification	Remove environmental hazards which may lead to fall	<ul style="list-style-type: none">• The lack of expert• Cost is high
PPE	Prevented fall-related physical injuries in a direct manner	<ul style="list-style-type: none">• User compliance is low• Not always effective
PERS	Enable emergency contact after falling	

2.4.3.1 The limitations of proactive fall prevention

Although the great effort has been carried out to promote effective proactive fall prevention strategies, there were still limitations. For fall risk assessment, it required a multi-disciplinary team to conduct assessment for an individual patient. Therefore, it was staff and resource intensive (Campbell and Robertson 2007). Some risk assessments were empirical and subjective that put their validity into question (Oliver et al., 2004). For home hazard modification, the difficulty of conducting this fall prevention measure was the lack of expert, who can successfully identify the hazards and make the necessary repairs or modifications (Scott et al., 2001). For strength and balance training, it had not reached a consensus on the optimal training requirements or programs, in terms of types of exercise and duration or intensity of exercise. The types of interventions must be developed and adopted with careful consideration of the individual's abilities because some programs may actually increase the fall risk. At least one exercise program, i.e., brisk walking for post-menopausal women, showed an increase in the number of falls (Ebrahim et al., 1997). At the same time, the strength training and balance intervention can be labor intensive and expensive for both individual and society. This makes such intervention clinically impractical. Additionally, certain risk factors, for example the aging process, cannot be effectively modified by any preventive strategies. Routine exercise and strength training certainly can slow down the aging effects by reducing the speed of functional decline or even regain some physiology capability among elderly. However, the aging and aging effect were irreversible.

2.4.3.2 The limitations in PPE and PERS

One major limitation in reactive fall prevention was user compliance. It was found that up to 75% of participants wore the PPE inconsistently and up to 50% refused to wear it (Kannus and Khan, 2001). Another concern was that PPE was not always effective. For example, hip fractures may occur before impact with the ground (Drinka, 1994). Studies showed that when people fell, the torso might pivot around a foot fixed to the ground. The torsional shearing forces generated during such a fall were considerable and were capable of shearing an osteoporotic hip (Drinka et al., 1993).

2.5 Fall detection

Fall detection, which may reduce fall-related injuries in an indirect manner, has recently been widely investigated. As an indirect and reactive fall prevention approach, fall detection can help ensure the timely arrival of medical attention with minimal human intervention, thereby reducing injury-related complications and mortalities. Fall detection can also automatically activate on-demand fall prevention systems (such as inflatable hip protectors) prior to the fall impact, which can prevent the physical injury.

Fall detection had been demonstrated to be an effective fall protection method that facilitated quick medical rescue or treatment to the fall victims. Gurley et al. (1993) reported a significant reduction in mortality rate if early detection and treatment was provided after falls among older people. Recent studies have also indicated that fall detection and the following immediate reporting to caregivers can certainly improve health outcome by initiating faster and appropriate medical care or evaluation (Rajendran et al., 2008). Besides, early detection of falls in the pre-impact phase can possibly

activate fall prevention devices (e.g. inflatable airbag) to avoid injuries caused by physical impacts with the ground (Shi et al., 2006; Tamura et al., 2009).

Fall incidents can be broken into three phases: pre-impact phase, impact and post-impact phase (Noury et al., 2008). During the pre-impact phase, loss of balance occurred and led to occasional sudden downward movement of the body. Therefore, the pre-impact fall detection algorithm aimed to distinguish falls and non-fall activities by detecting the sudden downward movement of human body. The impact fall detection was normally based on detecting the sudden polarity inversion of the acceleration vector during the impact (Williams et al., 1998) or the vibration of floors upon the impact (Litvak et al., 2008). Another class of fall detection methods was the post-impact mobility detection, which detected the situation when the fall person remained inactive on the ground (Noury et al., 2008). All the existing fall detection research and the fall detection methods were reviewed in details in the following sections. Figure 2-2 gave an outline of the following sections.

Figure 2-2 Outline for the review of fall detection research

2.5.1 Pre-impact detection

The main idea of pre-impact fall detection was to identify unique features of the velocity or acceleration profiles during the descending phase of a fall. Pioneer work was done by Wu (2000) who performed a video analysis of the movement of markers placed on the trunk of the participants. Wu (2000) found that vertical and horizontal speeds of the trunk were within a well-controlled range during ADLs but increased dramatically to three times higher during fall. Based on these findings, she set pre-determined threshold values at 1 m/s for both the vertical and horizontal speeds to discriminate the falls from ADLs. This was consistent with the findings from Hsiao and Robinovitch (1998) who

reported that the vertical velocity of the truck at descending phase of falls was within the range of 2-4 m/s. Similarly, Noury (2002) detected falls when the trunk movement velocity exceeded the threshold. And the transition from a vertical posture towards a lying posture was detected by the sensor module to confirm a fall incident.

Degen et al. (2003) introduced a fall detector in the form of wrist watch in which a tri-axis accelerometer was embedded. Falls were detected when a high downward velocity was noticed, followed by an impact within three seconds. After the impact, the faller's activity was monitored for 60 seconds. They tested it using only one participant and the overall successful detection rate was 65%. This was considered as very low compared with other fall detection algorithms. Similar threshold algorithm was employed by Bourke et al. (2007) who mounted three-axial accelerometers on the trunk and thigh to assess the peak accelerations during eight different types of falls. They reported that falls could be distinguished from ADLs based on a data set including 480 movements.

In Mathie et al. (2004), a tri-axial accelerometer was placed at the waist to detect the kinematic differences between ADLs and falls. They built a framework for the automated classification of human movement using this accelerometry monitoring system. Their framework yielded a sensitivity of 87% and specificity of 94%.

Nyan et al. (2008a) used wearable inertial sensors to detect faint falls in its incipience. They used three gyroscope sensors at three different locations: chest, pelvis and wrist for pre-impact fall detection. Linear acceleration and angular data were obtained and compared with pre-determined threshold values. Later, they used a three-axis accelerometer embedded in a garment-based system to implement the detection of signals of ADLs and falls. Results showed that all the simulated falls were detected

without false alarms, and $\sim 700\text{ms}$ lead-time was achieved by using their algorithm (Nyan et al., 2008b).

Kangas et al. (2008) had tri-axial accelerometers attached at the waist, wrist, and head. Their fall detection method was threshold based. The thresholds were set for total sum vector of acceleration, dynamic sum vector of acceleration, difference between the maximum and minimum acceleration and vertical acceleration for waist, wrist and head. They achieved a sensitivity of 97–98% and specificity of 100%. They further examined their algorithm by implementing a fall detector prototype placed at waist (Kangas et al. 2009), and claimed to achieve 80%- 97.5% sensitivity and 100% specificity for this prototype.

Dai et al. (2010) proposed a similar detecting algorithm. They calculated the total sum vector of acceleration ($\mathbf{A}_T$) and total sum vector of acceleration at the absolute vertical direction ($\mathbf{A}_v$). Their detection algorithm was based on comparing the difference of the maximum and minimum values of $\mathbf{A}_T$ and $\mathbf{A}_v$ with a predetermined threshold. Fall was detected if both the detection criteria were satisfied.

In Anania et al. (2008), fall was identified if the inclination angle of the trunk exceeded the threshold of 20 degrees and the inclination velocity of the trunk indicated a sudden variation. The sensitivity and specificity obtained from this study were 98% and 100%, respectively. Bourke et al. (2011) conducted a validation approach in order to determine a number of optimum temporal and angular parameter thresholds associated with falls performed in a quasi-realistic fall setting. For example, they reported that 99.05% of the “time-to-fall” measured during voluntary falls were less than 1.6s. The peak trunk angle appeared within a time window of -0.59s to 1.49s around the time point of the

impact. They also found that the selection of vertical acceleration threshold at 10m/s^2 can ensure 100% fall detection rate. They suggested these findings may be implemented in the future to build fall detection model.

2.5.2 Fall-impact detection

Another important way for fall detection was to detect the impact on the ground (or other obstacle) during falls. The impact was detected by the sudden polarity inversion of the acceleration vector that was also known as impact shock (Noury et al., 2008). Williams et al. (1998) designed a smart sensor embedded in the belt that could detect the impact shock as well as the horizontal position when a person lied down on the ground. Doughty et al. (2000) designed a similar device which used a two-stage fall detection model that included sensing impact shock and determining the orientation of the wearer. A fall was detected by an impact threshold and confirmed by the inclination of body within the 20 seconds after impact.

Lindemann et al. (2005) placed a tri-axial accelerometer into the hearing aid to detect fall. Trigger thresholds were pre-identified so that a fall alarm could be triggered when a sum-vector of acceleration in the vertical direction exceeded two gravity units during impact. Chen et al. (2005) designed a wearable sensors which can detect the impact difference during different activities including fall. The impact threshold to distinguish falls was set at three times of gravity. They also detected the change of orientation before and after the occurrence of fall to increase the fall detection accuracy. However, they did not report the key performance parameters, such as sensitivity and specificity.

Hwang et al. (2004) developed a chest wearable fall detector comprised of a tri-axial accelerometer, a gyroscope and a tilt sensor. The accelerometer was used to measure kinematic changes in three dimensions. The gyroscope was used to estimate posture transition, and tilt sensor to determine whether people were supine or standing. A fall was detected when the trunk acceleration changed rapidly (indicating the fall impact) followed by the tilt sensor leaned over 70 degrees.

Chao et al. (2009) used the impact detection in combination with post-fall posture detection. A fall was suspected by comparing the cross-product of instantaneous acceleration and reference acceleration (i.e. the acceleration measure when the people stand statically) with a threshold that was optimized base on the evaluation results. Then, a fall was considered to occur if trunk posture tilted more than 45° from the gravity line in a time window of 1.8s to 2.2s after a suspect fall (detected by the body impact). They achieved 100% sensitivity and 98% specificity.

Tolkiehn et al. (2011) reported a fall detection model based on detecting the sudden change of body angle and the acceleration peak during fall impact. They extracted the body rotation angles, the ratio of polar angle (i.e. the ratio of polar angle obtained at 80% of sampling window time over that obtained at 20% of sampling window time) and the body acceleration. They compared those parameters with an empirically determined threshold (however, they did not specify how to get this value). Nevertheless, they achieved 79.08% sensitivity and 83.33% specificity.

Another type of fall impact detection method relied on detecting the acoustic information or floor vibration. It was found that the acoustic information or floor vibration pattern caused by a fall impact was significantly different from those by normal

daily activities such as walking, tapping and also significantly different from those generated by fall objects (Alwan et al., 2006). Alwan et al. (2006) developed a floor vibration based fall detection system which could directly convert mechanical energy caused by the impact on the floor into an electrical signal by vibration sensors. With this system, falls could be detected with a sensitivity of 95% and specificity of 90%.

Similarly, Zhuang et al. (2009) analyzed the sounds made by the human body when hitting the ground. This approach can distinguish the fall from “human” and “other object” with sensitivity of 95%. Li et al. (2012a) proposed a system that can capture and enhance the sounds in a room for “fall” and “non-fall” activities classification. The height information was used to reduce the false alarm rate. They obtained a sensitivity of 100% and a specificity of 97%. They recently found that applying a genetic algorithm framework to perform the feature selection and MFCC calculation can improve the classification performance (Li et al., 2012b).

Zigel et al. (2009) proposed a fall detection model based on the combination of floor vibration and sound sensing. Temporal and spectral features were extracted from signals and a Bayes’ classifier was applied to classify fall and non-fall activities. They obtained sensitivity of 97.5% and specificity of 98.6%.

One limitation of floor vibration based fall detection was that experimental data were all obtained from controlled environment with hard and rigid floor condition (e.g. wooden floor surface). Under these controlled environments, the sounds or the vibration due to human fall impact were very distinctive and could easily be distinguished from dropped items such as a tray or a book. However, when the floor was covered with rugs or carpet, acoustic analysis become more difficult or even impossible (Grassi et al., 2008).

2.5.3 Post-impact detection

As many falls ended with the people lying on the ground, the simplest fall detection approach was detecting the posture change before and post falls (Hwang et al., 2004). Juang and Chang (2007), for example, detected the posture change from “stand” to “lie” based on a neural fuzzy network. The body silhouette was extracted and projected onto horizontal and vertical axes then a discrete Fourier transform was applied to each projected histogram. The magnitudes of significant Fourier transform coefficients together with the silhouette length-width ratio were used as the parameters for activities classification. They obtained average detection accuracy of 97.8%.

Another approach for post impact detection was to detect when both feet were no longer in contact with the ground (Noury et al., 2008). Tamura (2000) used this method to monitor fall incidents for normal adults and hemiplegic patients. However, there was an obvious shortcoming for fall detection by posture because horizontal lying was not necessarily associated with falls. One example was sleeping in a horizontal lying posture. Therefore, this method usually generated false alarms. Srinivasan et al. (2005) offered a complementary solution. They installed pressure sensitive floor tiles in their experimental environment that could detect the body lying on the floor first and then suggested a fall. Similarly, Depeursinge (2001) used the three orthogonally arranged accelerometers, which could locate the real-time spatial position of the device and, by training a neural network, could detect unusual events such as the fall of the wearer.

Post impact detection can be achieved by detecting the lack of movements after falls using sensors or cameras. Nait-Charif and Mckenna (2004) used over-heading video tracking cameras in a home environment to detect abnormal activities. The cameras could

detect inactive patterns resulted from falls. In Sixsmith et al. (2004), the information about the size, location, and velocity of the moving object (such as people) was determined using image-processing algorithms. Falls were detected based on the velocity and acceleration tracked by cameras. However, the reported detection rate was only 53%, which was rather low. The authors attributed the poor performance to inadequate training data for the neural network.

2.5.4 Fall detection algorithms

The sensor based threshold algorithm was the most commonly used fall detection algorithm in existing literature which had been applied in many above reviewed studies, such as Hwang et al. (2004), Bourke et al. (2008a), Bourke et al. (2008b) and Nyan et al. (2008b). The commonly used sensors include accelerometers and gyroscopes. For example, Jacob et al. (2011) implemented both accelerometer and gyroscope as a single unit. The threshold values were set for gravitational acceleration (2.73g), angular velocity (2.74rad/s) and angular acceleration (0.04 rad/sec^2) at three different locations (bony landmark of T-4, T-7 and T-10) along the thoracic vertebrae. They reported 100% sensitivity and 100% specificity.

Image processing techniques (or vision based) have been implemented on fall detection. Lee and Mihailidis (2005) developed a fall detection system based on a scene algorithm using video cameras mounted on the ceiling. They analyzed the 2D shape movement and the velocity of human body, and identified abnormal movement of the body during fall incidents through image processing and vector analysis. One hundred

and twenty-six fall-simulated tasks and 189 non-fall-simulated tasks were tested. The system was able to detect and miss falls on 77% and 23% of the occasions, respectively.

Rougier et al. (2007) attempted to detect falls by tracking the head movements. In their study, the head's velocity was tracked by a single video camera at the top corner of the experiment room. Fall incidence was detected by comparing velocities of the head (computed from its 3D trajectory in space) with pre-set thresholds. However, in this study, they did not report the pre-set threshold value and did not report their fall detection method.

Liu et al. (2010) adopted human body silhouette image for fall detection. They implemented a k-nearest neighbor classifier as the distinguish method. They also monitored the time needed for posture change to distinguish falls from normal lying down. They obtained sensitivity of 84.44%. Auvinet et al. (2011) proposed a novel method to detect falls at home based on a multiple-cameras network for reconstructing the 3D shape of human body. Falls were detected by analyzing the volume distribution of the 3D shape along the vertical axis and alarm was triggered when the major part of this distribution was abnormally near the floor during a predefined period of time (indicating the person has fallen on the floor). They achieved 99.7% of sensitivity and specificity. Other vision based fall detection methods were introduced by Cucchiara et al. (2004) and Nasution and Emmanuel (2007). Both used the normalized vertical and horizontal projection of body segment image for different activities classification.

Computational intelligence techniques, such as neural networks (Sixsmith et al., 2004) and fuzzy logic (Juang and Chang 2007), eigenspace techniques (Foroughi et al., 2008), and support vector machine (SVM) (Doukas et al., 2007) were used to classify

falls from ADLs. For example, Doukas et al. (2007) proposed a fall detection algorithm using SVM to classify the recorded movement data. Foroughi et al. (2008) proposed a fall detection approach based on the combination of integrated time motion images (ITMI) and eigenspace techniques and neural network. The activity recognition accuracy obtained from this study was between 83% and 97%.

Lai et al. (2009) developed a system composed of a predictor model estimated by an autoregressive process and a support vector machine (SVM) classifier. They used the digital signal from consecutive measurements of minimum toe clearance as the input for accurate detection of tripping gait characteristics. However, they did not investigate the fall detection accuracy. Similarly, Yu et al. (2012) also implemented SVM classifier to detect falls. Unfortunately, the performance evaluation was missing. Belshaw et al. (2011) compared three pattern recognition methods for fall detection, including logistic regression, neural network and SVM. They concluded the neural network achieved the best performance among those three with sensitivity of 92% and specificity of 95%. Abbate et al. (2012) implemented neural network to classified falls from other activities. They integrated the feature extract algorithm and the activities classifier into a smart phone. They involved the fall-like activities for model evaluation and reported 100% sensitivity and specificity. However, they only used simulated falls to test their detection model.

2.6 Summary of the limitations of existing fall detection research

Most of the pre-impact fall detection techniques were threshold based, but the detection threshold was arbitrarily predetermined without experimental basis. Typically,

a higher threshold would result in fewer false alarms but more misdetection, while a lower threshold would lead to less misdetection but more false alarms. Almost all the current fall detection techniques were facing this dilemma. Besides, the threshold should be dependent on the individual variability (Diaz et al., 2004). However, few studies had addressed this individual difference which further complicated the selection of fall detection threshold.

In addition, existing fall detection research focused only on distinguishing falls from simple ADLs. Some ADLs could be more complicated and fall-like (e.g. balance recovery from external perturbations). The fall detection model must be able to differentiate fall-like activities and falls as well in order to avoid false alarm.

Another limitation of existing fall detection research was to find optimal location for fall detection sensors. From another perspective, this limitation can be interpreted as there was lack of knowledge of the most appropriate fall indicators. It was reported that the sensor signals recorded at the time of the impact were significantly different for the sensors attached to different body parts (Mathie et al., 2004). To our knowledge, various body parts had been examined in this regard including the head (Kangas et al., 2007; Linderman et al., 2005), wrist (Bianchi et al., 2009; Cederstrom and Korhonen, 2007; Salomon et al., 2010), trunk (Li et al., 2009; Jacob et al., 2011), low back (Bourke et al., 2007; Mathie et al., 2004), thigh (Mathie et al., 2004; Sixsmith et al., 2004; Vishwakarma et al., 2007) and foot (Sim et al., 2011). However, no researcher had identified which body part was the optimal location for placement of fall detection sensors.

The current fall detection research was also limited by their external validity. The falls used for evaluating the fall detection model were often simulated. It was difficult to

generalize the experimental results obtained from a simulated fall to the general fall accidents that actually happened in daily life. Researchers had studied the fall of mannequins, voluntarily fall, and unexpected fall of human participants from a standing posture (Doughty, 2000; Bourke et al., 2008a; Nyan et al., 2008b). Such simulated falls must be different from fall accidents in real life, because most fall accidents occurred while the victims were in motion.

To overcome the limitations of existing fall detection methods, a novel pre-impact fall detection algorithm was developed and evaluated in this dissertation. Experimental study was conducted to investigate the whole body kinematics during slip-induced falls and non-fall activities. Thus, the appropriate fall indicators were identified through experiments. Realistic slip-induced falls were used instead of simulated fall for model evaluation. Data from successful recovery from slips, that were considered to be fall-like activities, were included for analysis. This fall detection algorithm was based on statistical process control chart which was established using individual historical data. Thus, this proposed fall detection model was individual-specific.

Chapter 3 Differentiating Slip-Induced Falls from Normal Walking and Successful Recovery after Slips using Kinematic Measures

Abstract

Fall detection can minimize the adverse consequences caused by falls. However, one limitation in the existing fall detection research is that the fall indicators were predetermined without any theoretical and experimental basis. This chapter determined the optimal fall indicators for fall detection research by experimentally examining a comprehensive set of kinematic measures. The body kinematic measures were compared among normal walking, successful recovery from slips, and slip-induced falls. In this chapter, the kinematic measures that differ between falls and the selected non-fall activities were identified at the early stage of loss-of-balance due to slips. Findings obtained from the present study can enhance the understanding of kinematic differences between slip-induced falls and non-fall activities, and such knowledge is particularly useful for developing fall detection models.

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3.1 Introduction

Knowledge of the biomechanics of slips especially during the phase of balance recovery can facilitate better understanding of slip mechanisms and further aid in effectively preventing falls due to slips (Redfern et al., 2001, Lockhart et al., 2003). Therefore, many recent studies have investigated biomechanics of slips during the phase of balance recovery (Liu and Lockhart, 2009; Yang and Pai, 2010; Yang et al., 2011; Qu et al., 2012). For example, it was found that corrective reactions during balance recovery after slips caused a reduction in the velocity of the slips foot, and thus improved the postural stability (Yang and Pai, 2010). Most recently, we have investigated the differences in lower extremity muscular responses between successful and failed balance recovery after slips, and found that successful balance recovery was associated with smaller muscular peak amplitude and smaller time-to-peak in the rectus femoris of the perturbed leg compared to failed balance recovery (Qu et al., 2012).

The knowledge of biomechanics of slips can facilitate developing fall detection models. Fall detection has been suggested to be able to protect fallers by minimizing injury severity during the occurrence of a fall (Bourke et al., 2007). Fall detection is effective in controlling fall hazards mainly from two aspects: initiating timely medical assistance for fallers and activating fall prevention device (e.g. inflatable airbag) to avoid physical impacts. Many recent attempts have been made to develop fall detection models (Wu 2000, Doukas et al., 2007, Nyan et al., 2008a, 2008b, Bagalà et al., 2012). For instance, Wu (2000) applied a threshold algorithm that used the vertical and horizontal speeds of the trunk as fall indicators to discriminate falls from activities of daily living. Doukas et al. (2007) proposed a fall detection model using the support vector machine

algorithm. They acquired foot accelerations in three directions as classification parameters and performed the activity classification to distinguish falls from simple walk and run. More recently, Nyan et al. (2008a, 2008b) have also developed a threshold-based fall detection model in which a fall was considered to occur if the linear acceleration and angular data obtained from torso and thigh exceeded the pre-determined threshold values.

The existing fall detection research was limited in terms of determining the optimal location(s) for the fall detection sensor(s). Since fall detection sensors are usually used to continuously monitor certain kinematic measures, this limitation can also be interpreted as that there is lack of knowledge of the most appropriate kinematic fall indicators. In fact, the fall indicators in existing fall detection models were predetermined without any theoretical and experimental basis.

To address this limitation, this chapter determined the optimal fall indicators for fall detection research by experimentally examining a comprehensive set of kinematic measures in terms of their ability to differentiate falls from non-fall activities. Since slips are one of the leading causes, so this study was focused on studying slip-induced fall detection. It was hypothesized that kinematic differences would exist between slip-induced falls and non-fall activities (i.e. successful recovery and normal walking), especially at the very early stage of loss-of-balance due to slips.

3.2 Methods

3.2.1 Participants

Sixty young participants including 30 males and 30 females (male participants: 24.3 ± 1.7 years, 175.2 ± 6.9 cm, 63.5 ± 8.4 kg; female participants: 24.1 ± 1.3 years, 163.1 ± 3.3 cm, 53.5 ± 8.1 kg) were recruited. Specific selections were made in order to balance across genders and to ensure diverse anthropometry among participants. Anthropometry information such as height and weight were obtained from each participant prior to the experiment. A questionnaire was used to ensure that participants were free from any medical conditions that may interfere with task performance or put them at an increased risk of injury during the experiment. All participants signed an informed consent form approved by the NTU Institutional Review Board.

3.2.2 Apparatus

An eight-camera motion capture system (Motion Analysis Eagle System, Santa Rosa, CA, USA) was used to collect the body kinematic data at the sampling rate of 100Hz. The collected data were filtered using a second order, zero-phase-lag, low-pass Butterworth filter with the cut-off frequency set at 10Hz. Standard footwear was provided to ensure the same floor coefficient of friction (COF) for every participant. To prevent injuries due to fall impacts, the participants were asked to wear a full body safety harness that was attached to a bearing on a ceiling mounted track by a pair of ropes. This protection is designed to permit participants to freely fall approximately ~ 50cm before being arrested so that their hands and buttocks could not contact the walkway surface. Pilot analysis has suggested that wearing the harness protection does not affect the

walking kinematics. Walking trials were conducted on a linear walkway (12m × 1.5m) which is covered by vinyl tiles.

3.2.3 Procedure

At the beginning of the experiment, reflective markers were placed on 26 anatomical landmarks (Figure 3-1). This marker placement scheme can help establish a 12-segment body model, which includes the head, upper arms, lower arms, trunk, thighs, shanks and feet. After that, the participants were given the opportunity to practice walking on the walkway. This practice also allowed the experimenters to determine the starting position so that the participants encountered the slippery surface at heel contact in slip trials.

Figure 3-1 Marker placement

During data collection, each participant was instructed to walk at the self-selected speed. In order to take attention away from the floor surface, the participants were instructed to look straight forward during walking. Meanwhile, the light was dimmed to prevent the awareness of changes in the walking surface. Four normal walking trials (i.e. without slips) and four slip trials were conducted in a random order with at least a three-minute break between consecutive trials. During the break, soles of the standard footwear were cleaned and participants were instructed to face the wall and listen to music to avoid detection of the experimenter changing the floor surface.

Slips were induced using a removable vinyl tile sheet (1.0m×1.2m, length×width) covered by water-detergent mixture (85% Dynamo Powereactive® plus 15% water). The vinyl material of the removable sheet was exactly the same as that of the walking surface. The removable sheet was randomly placed at one of four possible locations along the walkway (Figure 3-2) to avoid the participants' anticipation of the slips location. During slip trials, the vinyl tile didn't move in any direction. For each participant, falls would be identified if the midpoint between the left and right hip joint centers (estimated by the ASIS markers) dropped below 95% of its minimum height measured during normal walking (Beschorner and Cham 2008). Otherwise, balance recovery was considered to be successful.

Figure 3-2 Experiment set-up

3.2.4 Data reduction

In order to eliminate carry-over effects, only the first slip trial was selected from each participant. According to the balance recovery outcome, there were totally 23 successful recovery trials and 37 fall trials for analysis. At the same time, one normal walking trial (without slips) was randomly selected from each participant. The walking speed and stance duration for the selected trials were presented in Table 3.1. No significant differences in walking speed and stance duration were found among normal walking, successful recovery, and fall trials.

Table 3.1 Walking speed and stance duration for the selected trials: Mean (SD)

	Normal walking	Successful recovery	Slip-induced falls	<i>p</i> -value
Walking speed (m/s)	1.21 (0.31)	1.23 (0.34)	1.22 (0.36)	0.243
Stance duration (ms)	503 (232)	483 (219)	506 (202)	0.361

3.2.5 Dependent variables

To calculate dependent variables, a twelve-segment human body model was established first. The twelve segments, including bilateral upper arms, lower arms, thighs, shanks, feet, and unilateral head and trunk, were defined as rigid links connecting adjacent joint centers. The joint centers of the ankle, knee, elbow, and wrist were calculated as the midpoints of the markers at the corresponding lateral and medial bony landmarks. The hip joint center was estimated as locating at 14% of pelvic width medially, 24% of pelvic width posteriorly, and 30% of pelvic width inferiorly relative to the ASIS (Seidel et al., 1995). The shoulder centers were directly defined by the shoulder markers. The trunk segment was simplified as the link connecting the midpoints of the hip joint centers and the midpoints of the shoulder markers.

A global reference frame and segmental local center of mass (COM) frames were defined according to the ISB recommendations (Wu and Cavanagh, 1995). In the local segmental reference frames, the origin was fixed at the segmental COM with the $+X_i$ axis anterior, $+Y_i$ axis proximal, and $+Z_i$ being defined by the right-hand rule. For each body segment, the corresponding segmental COMs were estimated using the parameters provided by De Leva (1996). The origin of the global reference frame was fixed in the ground with $+X$ axis along the walking direction, $+Y$ axis upward and parallel with the field of gravity, and $+Z$ being defined by the right-hand rule.

Dependent variables in this study include three major categories of kinematic measures: segment translational measures, segment rotational measures, and joint angular

measures (Wu and Cavanagh, 1995). Segment translational measures were defined by the linear velocities and linear accelerations of the segmental COM. Segment rotational measures included segment rotational velocities and segment rotational accelerations. Similarly, joint angular measures included joint angular velocities and joint angular accelerations. As information on heel kinematics is critically important when studying biomechanics of slips (Redfern et al., 2001), slipped heel velocity and acceleration were also analyzed. Heel angular velocity and acceleration were assessed by foot segment rotational measures (Holbein-Jenny et al., 2007).

Body segment translational and rotational measures were calculated for the twelve body segments as indicated by the twelve-segment model. Body segment translational measures were presented along the three axes in the global reference frame. The linear velocity ($\dot{x}_i, \dot{y}_i, \dot{z}_i$) was calculated by differentiating the corresponding segmental COM displacement data with respect to the motion capture sampling interval (i.e. 0.01s). Similarly, the linear acceleration ($\ddot{x}_i, \ddot{y}_i, \ddot{z}_i$) was calculated using the time differentiation of the corresponding linear velocity. The segment rotational velocity ($\dot{\alpha}_i, \dot{\beta}_i, \dot{\gamma}_i$) and acceleration ($\ddot{\alpha}_i, \ddot{\beta}_i, \ddot{\gamma}_i$) were calculated using Euler angles (α, β, γ) accounting for the orientation of the corresponding segmental local frame with respect to the global reference frame. The Euler angles, α, β, γ , were ordered rotational measures about Z_i, Y_i , and X_i axes, respectively (Wu and Cavanagh, 1995).

There were ten bilateral joints of interest in this study, including the ankles, knees, hips, shoulders and elbows. The joint angles (θ) were calculated using Euler angles based on the rotation matrices between the two corresponding adjacent local reference frames. We reported the hip and shoulder joint angular measures in three dimensions: flexion-

extension (F/E), abduction-adduction (A/A), and internal-external rotations (I/E). For the ankles, knees and elbows, only the flexion-extension measures were reported, since abduction-adduction and internal-external rotations of these joints are much smaller compared to flexion-extension (Chaffin et al., 1999). A detailed description of the notations for dependent variables is as following:

Segment translational measures:

$\dot{x}_i, \dot{y}_i, \dot{z}_i$: segment linear velocities along the global X, Y, Z axes, respectively.

$\ddot{x}_i, \ddot{y}_i, \ddot{z}_i$: segment linear accelerations along the global X, Y, Z axes, respectively.

Segment rotational measures:

$\dot{\alpha}_i, \dot{\beta}_i, \dot{\gamma}_i$: ordered rotational velocities about Z_i , Y_i , and X_i axes, respectively.

$\ddot{\alpha}_i, \ddot{\beta}_i, \ddot{\gamma}_i$: ordered rotational accelerations about Z_i , Y_i , and X_i axes, respectively.

Joint angular measures:

$\dot{\theta}_j$: joint angular velocity.

$\ddot{\theta}_j$: joint angular acceleration.

i = SS-Foot, NS-Foot, SS-Shank, NS-Shank, SS-Thigh, NS-Thigh, Trunk, Head, SS-UpperArm, NS-UpperArm, SS-LowerArm, NS-LowerArm;

j = SS-Ankle, NS-Ankle, SS-Knee, NS-Knee, SS-Hip, NS-Hip, SS-Shoulder, NS-Shoulder, SS-Elbow, NS-Elbow;

SS = Slip side; NS = Non-slip side.

All the dependent measures are illustrated in Figure 3-3 to Figure 3-5. In particular, Figure 3-3 shows all the segment translational measures. The coordinate system in each body segment indicates the local segmental reference frame. The coordinate system with capital X, Y, Z on the floor indicates the global reference frame. In this diagram, it is indicating that the right-hand side is identified as the slip side. Similarly, Figure 3-4 shows all the segment rotational measures and Figure 3-5 shows all the joint angular measures.

Figure 3-3 Illustration of segment translational measures

Figure 3-4 Illustration of segment rotational measures

Figure 3-5 Illustration of joint angular measures

3.2.6 Statistical analysis

The independent variable here was ‘activities’, which had three levels: normal walking, successful recovery, and falls (i.e. failed recovery). For the normal walking trials (i.e. non-slip trials), kinematic data under analysis were randomly selected from a complete stance phase during a gait cycle. The analyzed kinematic data for the slip trials (i.e. either successful recovery or falls) were those chosen from heel contact (i.e. when the heel of the slip foot struck the slippery surface) to recovery (i.e. marked as the end of

the unilateral slip) or fall completion (i.e. when the body was completely supported by the harness). Given that there existed temporal differences in gait cycles between trials, the time for the analyzed data in each experimental trial (i.e. both slip trials and normal walking trial) was normalized by the mean duration of the stance phase of the normal walking gait cycles with 0% being heel contact. Doing so allowed us to make comparisons between trials and between different levels of activities (i.e. falls, successful recovery, and normal walking).

A critical fall detection performance measure is detection time, which is defined as the time difference between fall initiation and fall detection and is used to indicate how rapidly the fall detection system will respond to a fall. Knowing how soon a kinematic measure can differentiate falls from non-fall activities can aid in determining the kinematic fall indicator that may be associated with short detection time. Thus, the kinematic responses in the early stance phase right after being slipped are of particular interest. Therefore, univariate analysis of covariance (ANCOVA) was performed on the dependent variables at the selected equally-divided discrete points in the early stance phase (0% ~ 30% into stance phase) with the walking speed as a covariate. The interval between two consecutive discrete points was 2% into stance (i.e. 2%, 4%, 6%, ..., 30%). Given the large number of dependent variables, in order to minimize the probability of type I error, the level of significance (α) was set at 0.01 throughout the analysis.

Through the ANCOVA, we were able to determine the dependent variables that became significantly different among ‘activities’ in the early stance phase. To distinguish falls from other activities (i.e. successful recovery and normal walking), post hoc pairwise comparisons using the Bonferroni correction were further conducted on the

dependent variables that were found to be significantly different among ‘activities’. Further, in order to achieve reliable detection of the differences, effect sizes quantified by Cohen’s d were calculated for the dependent variables that were found to be able to differentiate falls from other activities at three consecutive discrete points (or more). The effect size is the strength or magnitude of the difference between two data sets. The larger the effect size is, the easier a difference between two data sets can be detected. The small, medium, and large effect sizes were suggested to be corresponding to 0.2, 0.5, and 0.8, respectively (Cohen 1992). Statistical analyses were all performed using MATLAB™ statistic toolbox (The MathWorks, Natick, MA, USA).

3.3 Results

Results from the ANCOVA showed that 55 dependent variables were significantly different across three ‘activities’ levels (p -value <0.01) in the early stance phase (Table 3.2). Table 3.2 showed that statistical difference was found for 21 segment linear velocity measures at different phase of early stance (rang from 12%-26% of stance) and 14 segment linear acceleration measures at different phase of early stance (rang from 14%-26% into stance). In total, 35 linear segmental measures were significantly different across three ‘activities’ levels. Eighteen of them were upper body kinematic measures (head, upper arms, lower arms and trunk), the rest were lower body kinematic measures (thigh, shank and foot). Statistical difference was also found for 15 segment rotational measures and 5 joint angular measures at different phase of early stance (rang from 14%-26% of stance). This included 10 segment rotational velocity measures from head, upper

arm, thigh, shank and foot; 5 segment rotational acceleration measures from head, trunk, thigh and shank; and 5 joint angular measures from shoulder, hip, knee and ankle.

Post-hoc multiple comparisons further revealed that 13 dependent variables were significantly different between falls versus normal walking and successful recovery (Table 3.3). In other words, 13 dependent variables were able to statistically distinguish falls from non-fall activities in the early stance phase.

Table 3.2 Summary of the segment linear velocity results from the ANCOVA (Mean $\pm$ SD). ‘Point of % into stance’ indicates the earliest moment when significant difference among ‘activities’ was found in the early stance phase.

Dependent variables	Point of % in normal stance walking	Recovery	Fall	<i>p</i> -values for the independent variable	<i>p</i> -values for the covariate	
Segment linear velocity (Unit: m/s)						
$\dot{x}_{Head}$	18	1.308±0.144	1.254±0.334	1.299±0.320	<0.001	0.233
$\dot{y}_{Head}$	14	0.085±0.084	-0.013±0.091	-0.031±0.017	0.003	<0.001*
$\dot{y}_{NS-UpperArm}$	18	0.111±0.137	-0.091±0.131	-0.428±0.218	<0.001	0.104
$\dot{z}_{NS-UpperArm}$	18	0.102±0.036	0.108±0.047	-0.101±0.088	0.005	0.134
$\dot{x}_{NS-LowerArm}$	18	1.820±0.413	1.263±0.342	1.211±0.534	0.007	0.441
$\dot{z}_{NS-LowerArm}$	18	0.073±0.061	-0.217±0.343	-0.345±0.351	0.004	0.135
$\dot{x}_{SS-LowerArm}$	14	0.751±0.412	2.123±1.012	2.412±1.412	0.008	0.322
$\dot{y}_{SS-LowerArm}$	26	0.048±0.049	-0.481±0.323	-0.417±0.329	0.004	0.203
$\dot{x}_{Trunk}$	20	1.403±0.213	1.031±0.351	1.104±0.421	0.005	0.004*
$\dot{y}_{Trunk}$	16	0.382±0.026	0.202±0.212	-0.106±0.023	<0.001	0.234
$\dot{z}_{Trunk}$	24	0.033±0.034	0.104±0.032	0.121±0.045	0.007	0.024
$\dot{x}_{NS-Thigh}$	14	1.624±0.322	2.019±0.341	2.046±0.341	0.004	0.023
$\dot{y}_{NS-Thigh}$	16	0.062±0.034	0.093±0.046	-0.298±0.215	0.005	<0.001*
$\dot{x}_{SS-Thigh}$	16	1.442±0.512	0.712±0.321	1.047±0.241	0.003	0.431
$\dot{x}_{NS-Shank}$	24	0.062±0.313	2.139±0.341	1.502±0.218	0.006	<0.001*
$\dot{x}_{SS-Shank}$	16	0.170±0.597	0.829±0.302	1.161±0.723	0.005	0.811
$\dot{z}_{SS-Shank}$	22	0.017±0.017	-0.121±0.410	0.503±0.313	0.004	0.001*
$\dot{x}_{NS-Foot}$	12	0.312±0.412	3.123±2.431	3.512±2.411	0.003	0.002*
$\dot{y}_{NS-Foot}$	22	0.143±0.312	-1.201±1.011	-1.029±1.123	0.003	0.187
$\dot{x}_{SS-Foot}$	28	2.891±2.001	0.040±0.879	1.381±1.449	0.002	0.185
$\dot{x}_{SS-Heel}$	20	0.131±0.234	0.412±0.239	0.513±0.211	0.002	0.001*

Table 3.2 Summary of the segment linear acceleration results from the ANCOVA (Mean $\pm$ SD). ‘Point of % into stance’ indicates the earliest moment when significant difference among ‘activities’ was found in the early stance phase.

Dependent variables	Point of into stance	normal walking	Recovery	Fall	<i>p</i> -values for the independent variable	<i>p</i> -values for the covariate
Segment linear acceleration (Unit: m²/s)						
$\ddot{x}_{Head}$	24	-0.821 $\pm$ 0.743	-3.101 $\pm$ 2.013	-3.812 $\pm$ 2.313	0.004	0.124
$\ddot{y}_{Head}$	18	0.011 $\pm$ 0.103	-0.02 $\pm$ 0.212	-0.091 $\pm$ 0.834	0.007	0.312
$\ddot{x}_{NS-Upperarm}$	14	1.031 $\pm$ 0.312	2.312 $\pm$ 1.763	-0.377 $\pm$ 1.873	0.007	0.341
$\ddot{z}_{NS-Lowerarm}$	18	-0.042 $\pm$ 0.124	-2.093 $\pm$ 2.003	-2.412 $\pm$ 1.312	0.003	0.004*
$\ddot{y}_{SS-Lowerarm}$	28	1.051 $\pm$ 0.948	7.091 $\pm$ 4.123	1.512 $\pm$ 3.124	0.005	0.211
$\ddot{y}_{Trunk}$	18	2.312 $\pm$ 1.031	-1.031 $\pm$ 1.213	-3.123 $\pm$ 2.133	<0.001	0.123
$\ddot{z}_{Trunk}$	13	-1.645 $\pm$ 0.495	-0.450 $\pm$ 0.932	0.115 $\pm$ 0.912	0.005	0.151
$\ddot{x}_{NS-Shank}$	14	-8.123 $\pm$ 2.312	6.232 $\pm$ 6.453	6.075 $\pm$ 5.412	0.005	0.142
$\ddot{y}_{NS-Shank}$	18	1.650 $\pm$ 0.952	-8.124 $\pm$ 4.502	-7.850 $\pm$ 5.081	0.008	0.412
$\ddot{x}_{SS-Shank}$	14	-2.922 $\pm$ 1.459	0.541 $\pm$ 1.319	0.702 $\pm$ 2.019	0.004	0.430
$\ddot{x}_{NS-Foot}$	18	0.034 $\pm$ 0.873	15.312 $\pm$ 4.023	18.124 $\pm$ 6.912	0.001	<0.001*
$\ddot{y}_{NS-Foot}$	18	3.014 $\pm$ 0.981	-12.142 $\pm$ 8.081	-11.423 $\pm$ 5.912	0.003	0.031
$\ddot{z}_{SS-Foot}$	18	-0.131 $\pm$ 0.258	1.851 $\pm$ 2.038	1.834 $\pm$ 3.035	0.007	0.312
$\ddot{x}_{SS-Heel}$	26	3.106 $\pm$ 3.194	7.412 $\pm$ 3.345	8.489 $\pm$ 3.308	0.008	0.341

Table 3.2 Summary of the segment rotational measures results from the ANCOVA (Mean $\pm$ SD). ‘Point of % into stance’ indicates the earliest moment when significant difference among ‘activities’ was found in the early stance phase

Dependent variables	Point of into stance	normal walking	Recovery	Fall	<i>p</i> -values for the independent variable	<i>p</i> -values for the covariate
Segment rotational velocity (Unit: degree/s)						
$\dot{\alpha}_{Head}$	26	13.803 $\pm$ 10.028	-3.463 $\pm$ 8.123	-8.091 $\pm$ 12.134	0.001	0.005*
$\dot{\gamma}_{SS-Upperarm}$	20	22.141 $\pm$ 13.532	-13.341 $\pm$ 13.330	-9.8304 $\pm$ 13.012	0.005	0.492
$\dot{\alpha}_{SS-Thigh}$	14	-48.626 $\pm$ 12.802	-6.631 $\pm$ 4.058	-12.541 $\pm$ 13.141	0.007	<0.001*
$\dot{\gamma}_{SS-Thigh}$	22	6.120 $\pm$ 4.123	-4.123 $\pm$ 12.123	-6.173 $\pm$ 10.912	0.007	0.592
$\dot{\gamma}_{NS-Shank}$	14	14.054 $\pm$ 3.123	-12.391 $\pm$ 8.108	-14.036 $\pm$ 13.912	0.004	0.412
$\dot{\alpha}_{SS-Shank}$	18	-21.376 $\pm$ 25.766	-5.801 $\pm$ 14.123	-4.311 $\pm$ 13.134	0.008	0.495
$\dot{\alpha}_{NS-Foot}$	16	-20.073 $\pm$ 15.414	12.985 $\pm$ 11.597	18.880 $\pm$ 15.268	<0.001	0.009*
$\dot{\gamma}_{NS-Foot}$	20	12.587 $\pm$ 13.901	71.013 $\pm$ 13.934	79.001 $\pm$ 12.973	0.004	0.489
$\dot{\alpha}_{SS-Foot}$	24	12.312 $\pm$ 8.125	-12.013 $\pm$ 13.131	-20.390 $\pm$ 20.994	0.001	0.301
$\dot{\gamma}_{SS-Foot}$	20	-4.312 $\pm$ 8.123	-2.134 $\pm$ 7.091	5.013 $\pm$ 10.953	0.005	<0.001*
Segment rotational acceleration (Unit: degree²/s)						
$\ddot{\gamma}_{Head}$	20	-7.230 $\pm$ 3.134	-9.120 $\pm$ 13.131	-9.123 $\pm$ 4.911	0.009	0.134
$\ddot{\alpha}_{Trunk}$	18	0.810 $\pm$ 2.094	0.031 $\pm$ 4.013	0.023 $\pm$ 4.091	0.003	0.412
$\ddot{\gamma}_{Trunk}$	22	2.131 $\pm$ 3.124	-0.195 $\pm$ 4.981	-0.284 $\pm$ 3.913	0.004	0.834
$\ddot{\alpha}_{SS-Thigh}$	18	13.233 $\pm$ 14.912	6.913 $\pm$ 11.134	8.154 $\pm$ 10.921	0.007	<0.001*
$\ddot{\alpha}_{NS-Shank}$	18	20.098 $\pm$ 20.913	34.103 $\pm$ 38.013	19.013 $\pm$ 23.313	0.001	0.003*
Joint angular velocity (Unit: degree/s)						
A/A $\dot{\theta}_{SS-Shoulder}$	16	12.210 $\pm$ 3.341	5.139 $\pm$ 3.912	5.912 $\pm$ 4.918	0.005	0.131
A/A $\dot{\theta}_{SS-Hip}$	28	-6.446 $\pm$ 3.755	-4.012 $\pm$ 5.212	-4.401 $\pm$ 4.124	0.001	0.812
I/E $\dot{\theta}_{SS-Hip}$	16	-7.481 $\pm$ 3.556	2.012 $\pm$ 3.124	3.012 $\pm$ 3.861	0.004	0.103
F/E $\dot{\theta}_{SS-Knee}$	20	-21.801 $\pm$ 13.031	-12.302 $\pm$ 7.634	-14.098 $\pm$ 8.892	0.004	0.134
F/E $\dot{\theta}_{SS-Ankle}$	22	-3.721 $\pm$ 1.329	-12.123 $\pm$ 5.9123	-10.234 $\pm$ 7.923	0.007	0.445

Table 3.3 Summary of the results from post-hoc multiple comparisons. Lower bound and upper bound define the 99% confident interval for the mean difference of the measure between two activities. Significant difference is determined if the 99% confident interval does not contain zero. The point of % into stance indicates the earliest moment when significant difference between falls and non-fall activities was found in the early stance phase.

Dependent variables	Point of % into stance	Normal walking vs. successful recovery		Normal walking vs. falls		Successful recovery vs. falls	
		lower bound	upper bound	lower bound	upper bound	lower bound	upper bound
Segment linear velocity (Unit: m/s)							
$\dot{x}_{Head}$	24	0.024	0.109	0.148	0.327	0.026	0.233
$\dot{y}_{Head}$	22	0.014	0.269	0.007	0.713	0.021	0.152
$\dot{y}_{NS-UpperArm}$	18	0.044	0.417	-0.518	-0.001	-0.077	-0.005
$\dot{y}_{Trunk}$	18	-0.050	0.224	-0.405	-0.241	-0.270	-0.098
$\dot{x}_{SS-Thigh}$	16	0.026	0.046	0.423	0.689	0.605	0.662
$\dot{x}_{SS-Shank}$	16	0.065	0.501	1.435	1.973	1.376	1.400
Segment linear acceleration (Unit: m ² /s)							
$\ddot{y}_{Head}$	22	-0.882	-0.114	0.052	0.969	-1.028	-0.347
$\ddot{x}_{NS-UpperArm}$	14	0.006	0.212	0.009	0.384	-2.210	-0.030
$\ddot{y}_{Trunk}$	16	-1.981	-0.231	-1.777	-0.355	-1.526	-1.000
Segment orientation velocity (Unit: degree/s)							
$\dot{\alpha}_{Head}$	26	-0.012	0.075	0.048	0.065	0.013	0.019
$\dot{\gamma}_{SS-UpperArm}$	24	-0.121	0.083	0.016	0.026	0.012	0.155
$\dot{\alpha}_{SS_Thigh}$	16	-0.031	0.031	-0.060	-0.014	-0.057	-0.027
$\dot{\alpha}_{SS_Shank}$	18	-0.052	0.023	-0.153	-0.003	-0.146	-0.006

The results on effect size were showed in Table 3.4. The effect sizes for the comparisons of falls versus recovery and falls versus normal walking were large (i.e. >0.8) for five dependent variables. These dependent variables were $\dot{y}_{NS-UpperArm}$, $\dot{y}_{Trunk}$, $\dot{x}_{SS-Shank}$, $\ddot{y}_{Head}$ and $\dot{a}_{Head}$.

Table 3.4 Effect sizes. * indicates large effect size (>0.80).

Measures	Normal walking vs. successful recovery	Normal walking vs. falls	Successful recovery vs. falls
Segment linear velocity (Unit: m/s)			
$\dot{x}_{Head}$	0.47	1.09*	0.73
$\dot{y}_{Head}$	0.53	0.96*	0.76
$\dot{y}_{NS-UpperArm}$	1.34*	1.44*	1.49*
$\dot{y}_{Trunk}$	1.42*	1.39*	1.13*
$\dot{x}_{SS-Thigh}$	0.60	0.57	0.30
$\dot{x}_{SS-Shank}$	1.56*	1.16*	0.99*
Segment linear acceleration (Unit: m²/s)			
$\ddot{y}_{Head}$	1.36*	0.94*	1.04*
$\ddot{x}_{NS-UpperArm}$	2.74*	0.82*	0.66
$\ddot{y}_{Trunk}$	0.41	0.85*	0.41
Segment orientation velocity (Unit: degree/s)			
$\dot{a}_{Head}$	1.79*	1.32*	1.69*
$\dot{y}_{SS-UpperArm}$	0.77	0.19	0.67
$\dot{a}_{SS-Thigh}$	0.32	0.72	0.43
$\dot{a}_{SS-Shank}$	0.27	0.74	0.81*

The mean profiles of the dependent variables with large effect sizes were shown in Figure 3-6, according to which the vertical kinematic measures (i.e. $\dot{y}_{NS-UpperArm}$, $\dot{y}_{Trunk}$, and $\dot{y}_{Head}$) among the three levels of ‘activities’ tended to slightly increase right after heel contact and then decrease. Such decreasing changes were more substantial for

falls compared to normal walking and successful recovery. There was a more dramatic change in $\dot{x}_{SS-Shank}$ at nearly 15% into stance for falls compared to other activities. Falls also resulted in a dramatic decrease in $\dot{a}_{Head}$ between 15% and 20% into stance.

Figure 3-6 Mean profiles of kinematic measures with large effect sizes.

3.4. Discussion

One hundred and eighty-two kinematic measures covering the whole body segments and major joints were examined during slip-induced falls, successful recovery after slips, and normal walking in the present study. Thirteen measures were found to be significantly different between falls and non-fall activities (i.e. successful recovery and normal walking) within the normalized time range between 0% and 30% into stance. These findings could be used to explain why some of previous fall detection studies were successful in detecting falls. For example, Wu (2000) and Mathie et al. (2004) chose the trunk vertical velocity as a fall indicator, while the $\dot{y}_{Trunk}$ was found to be significantly different between falls and other activities in our study.

Previous fall detection applications mainly focused on examining fall kinematics in the sagittal plane (Wu, 2000; Nyan et al., 2008a). These applications can be supported by the results from the present study, which showed that no segment translational measures along the global Z axes were significantly different between falls and non-fall activities. These results provided evidence that it might be difficult to detect the difference between falls and successful recovery using medial-lateral measures in practice.

Kinematic measures of some segments such as the upper arms and shanks were rarely investigated in previous studies. However, according to our findings, some kinematic measures of the upper arms, shanks, and head were significantly different between successful and failed recovery attempts. Therefore, the upper arms, shanks and head could also be desirable body sites for locating fall detectors.

Linear accelerations may not be good at distinguishing falls from other activities, given that only three linear acceleration measures were presented in Table 3.3. Actually,

many acceleration measures were significantly different among ‘activities’ (Table 3.2). However, such significant differences mostly occurred between slip trials and normal walking trials. In other words, most of the acceleration measures were not significantly different between successful and failed balance recovery after slips. Some of earlier fall detection research used acceleration measures as fall indicators (Bourke et al., 2007; Nyan et al., 2008b), and still reported good fall detection performance. However, to our knowledge, none of these studies compared falls with fall-like activities (e.g. successful recovery after slips). The results of this study may suggest that fall detection based on acceleration measures could not perform well in distinguishing falls from fall-like activities, and further emphasize the importance of selecting appropriate fall indicators when developing fall detection models.

Even though there were significant differences in some kinematic measures between slip-induced falls and non-fall activities, it is not necessary that the sizes of the differences be practically meaningful. In other words, the significant differences between falls and other activities may not be large enough to be easily detected. To address this, effect sizes of the kinematic measures were estimated using Cohen’s *d*. Five measures, including $\dot{y}_{NS-UpperArm}$, $\dot{y}_{Trunk}$, $\dot{x}_{SS-Shank}$, $\dot{y}_{Head}$ and $\dot{a}_{Head}$ were found to have large effect sizes (i.e. Cohen’s *d*>0.8, Table 3.4). Such findings suggest that in order to achieve high sensitivity and specificity of fall detection, we could select these five measures as fall indicators.

Further, in fall detection models, lead time (defined by the time interval between detecting the fall and the end of the fall) is used to determine how rapid a fall detection model responds to a fall. In practice, larger lead time indicates more time available for

protective systems (e.g. inflatable airbag) to be activated before fall impact. Therefore, there is a need to identify which kinematic variable is able to detect falls soonest. Among the measures with large effect sizes, we found that $\dot{x}_{SS-shank}$ was able to tell the differences between falls and other activities as early as 16% into stance. This finding suggests that the use of $\dot{x}_{SS-shank}$ as a fall indicator may result in largest lead time compared to other measures. Although it may be argued that the reliance on a single measure to detect falls would decrease the robustness of the fall detection system, this finding does indicate the possibility of early detection of ‘abnormal’ changes leading to falls.

Cham and Redfern (2002b) reported differences in peak heel velocity between successful recovery and falls. However, in our study, we did not find that heel velocity was able to differentiate slip-induced falls from non-fall activities. The discrepancy between our study and Cham and Redfern (2002b) can be explained from two perspectives. First, our study and Cham and Redfern (2002b) used different criteria to differentiate successful recovery and slips-induced falls. Specifically, Cham and Redfern (2002b) used the slip distance to categorize the outcome of walking trials into non-slip, slip-recovery, and slip-fall. But in our study, falls were identified if the midpoint between the left and right hip joint centers dropped below 95% of its minimum height measured during normal walking (Beschorner and Cham 2008). Second, Cham and Redfern (2002b) examined the peak value of heel velocity. They also reported the differences in time-to-peak among different events. In other words, the peak heel velocity among different events occurs at different time points. In our study, we aimed to identify the kinematic measures that can differentiate falls from non-fall activities in a real-time manner.

Therefore, we compared instantaneous kinematic measures rather than peak values among normal walking, successful recovery, and falls.

In a recent study (Beschorner et al., 2012), knee kinematics deviation was found during slips at approximately 110-120 ms after heel contact. However, the comparisons were done only between non-slip trials and slip trials. Beschorner et al. (2012) did not compare between successful recovery and slip-induced falls. The ANCOVA results in our study also revealed significant differences in knee angular velocity among the three levels of ‘activities’ (Table 3.2). But, significant differences were not found between successful recovery and slip-induced falls.

The selected activities were considered to be representative of falls, fall-like activities, and activities of daily living, respectively. In particular, a slip-induced fall is one of the most common types of falls; successful recovery is fall-like since it shares some similar kinematic characteristics with falls; normal walking is the most common daily activity of living. A limitation of this study was that only three activities were compared. More activities need to be examined in future work in order to better generalize the research findings into real life.

Another limitation of this study is that the filtering schemes in this study would not be possible in true real time fall detection equipment. Specifically, the zero-phase filter utilizes past and future information to remove high frequency noise from the signal. In real time fall detection, future information is not available and so a different filtering scheme would need to be implemented. One solution to this issue would be to incorporate a time delay in the monitoring of fall indicators so that the zero-phase filter could consider the signal from earlier and later time events. A significant time-delay could be

built into the fall detection devices given that lead time is typically about 500 ms (Nyan et al., 2008a, 2008b; Wu, 2000). Additional research would be needed to determine the effects of the time delay size on the sensitivity and specificity of the system.

A good fall indicator in fall detection models must have three features so as to achieve good fall detection performance. First, the fall indicator must be able to differentiate falls from activities of daily living. Second, the differences quantified by the fall indicator between falls and activities of daily living must be large enough to be detected. Third, the fall indicator should facilitate detecting falls quickly. Without the first feature, fall detection itself would become impossible. The second feature would ensure that fall detection performance assessed by sensitivity and specificity would be desirable. The third feature would lead to short detection time and large lead time. In the present study, we examined a comprehensive set of body kinematic measures during balance recovery after slips and attempted to determine the kinematic measures that have the abovementioned features. Thus, findings from the present study could help determine the optimal fall indicators in fall detection models so as to obtain desirable fall detection performance. To our knowledge, this study is the first attempt to investigate the optimal fall indicators through experimental studies and statistical analysis. As slip-induced falls are serious and prevalent in workforce, we believe that findings from the present study are able to help develop effective strategies to prevent injuries caused by accidental falls.

Chapter 4 An Individual-Specific Fall Detection Model based on the Statistical Process Control Chart

Abstract

As an important method to protect fallers by minimizing injury severity, fall detection has been widely studied. However, there are some common limitations in existing fall detection models. In particular, the fall indicators and detection thresholds were arbitrarily predetermined without any theoretical and/or experimental basis, and most fall detection model cannot address inter-individual differences. This study presents a novel pre-impact fall detection model based on the statistical process control chart that is able to address the existing limitations. The fall indicators in this model were selected based on experimental findings. The fall detection model is individual-specific, since it is constructed using individual historical movement data. The fall detection model demonstrates a high accuracy with up to 94.7% sensitivity and 99.2% specificity. In addition, this model can also provide sufficient time for triggering fall protection device in the pre-impact phase, thus potentially effective in preventing fall injuries.

* This chapter has been published in *Safety Science*. Hu and Qu (2014)

4.1 Introduction

The existing fall detection methods are mainly threshold-based (Bourke et al., 2007; Noury, 2000; Rougier et al., 2007; Wu, 2000). For instance, in Wu (2000), a fall was detected if both the vertical and horizontal trunk velocity exceeded 1 m/s. Similarly, Noury (2000) also used the trunk velocity as one of the fall indicators and a fall was considered to occur if the trunk vertical velocity exceeded a pre-determined threshold. More recently, Bourke et al. (2007) have simulated eight different types of falls and eight-different types of activities of daily living (ADLs) in a laboratory setting. Trunk and thigh kinematics were measured by three-axial accelerators attached to the trunk and thigh, respectively. The fall detection thresholds were defined by the smallest positive and negative peaks of the trunk and thigh resultant accelerations during simulated falls. They reported that falls could be distinguished from ADLs based on a data set including 480 movements.

Although threshold-based fall detection methods have been widely investigated, there are some common limitations in the existing methods. Firstly, the fall indicators and detection thresholds were arbitrarily predetermined without any theoretical and/or experimental basis. The selection of fall indicators and detection thresholds directly affects the fall detection performance. Secondly, the existing fall detection methods cannot address inter-individual differences. However, it is well known that different individuals may have different motion patterns and characteristics. Further, only voluntary falls were simulated in the existing fall detection studies, while accidental falls in reality were mainly involuntary in nature. Thus, external validity of the existing fall detection studies is questionable.

Chapter 3 has identified the appropriate fall indicators. This chapter aimed to develop a novel fall detection model that is able to address the existing limitations in fall detection. The statistical process control chart that has been widely used in the field of quality control (Woodall et al., 2004; Haridy and Wu, 2007; Mohammed et al., 2008) can effectively detect the abnormal changes in system performance by tracking the process performance over time. Fall detection shares some common features with quality control in terms of data collection and abnormality detection. Thus, the novel fall detection model presented here was based on the statistical process control chart. Slips are one of the most common causes leading to accidental falls and nearly 70% of falls occur during walking (Lloyd and Stevenson, 1992). Thus, the proposed model was developed to detect slip-induced falls during locomotion. Besides addressing the limitations in the existing fall detection methods, the proposed model was also expected to be associated with high sensitivity and specificity.

4.2 Introduction to the statistical process control chart

4.2.1 Conventional statistical process control

The conventional statistical process control chart is based on the theoretical concept of Shewhart statistical process control (Shewhart, 1931) which indicates that if a process is under statistical process control, the future variation of such process can be predicted within limits (Shewhart, 1939) and the abnormal variation (also called special cause) is detected when the data are out of the limits. These control limits define the natural range of variation. In general, there are an upper and a lower limit which are obtained from historical data and represent the limits of the under-controlled state of

certain activities. Any points falling outside of these control limits indicate the occurrence of abnormal activities. In a common practice of Shewhart individual control chart, the “three sigma control limits” are obtained, where the control limits are defined by three times of the standard deviation (Shewhart, 1931). Previous industrial applications have demonstrated that the Shewhart statistical process control chart is a simple and powerful tool to detect the sudden and substantial changes in data without frequent false alarms (Montgomery, 2008; Woodall et al., 2004; Benneyan et al., 2003; Haridy and Wu, 2009).

There was considerable interest of applying the statistical process control chart in healthcare (Mohammed et al., 2008; Woodall et al., 2004). For example, the statistical process control chart was implemented to monitor the occurrence of rare health-related events such as infection rates and rates of patient falls in daily hospital settings (Lee and McGreevey, 2002; Woodall et al., 2004). The abnormally high occurrence rate was used as the reference for assessing hospital performance and development. Process monitoring with the control chart has been increasingly used and recognized as an important component for evaluating and improving the healthcare performance.

4.2.2 Limitations of the conventional statistical process control chart

A standard and important assumption when applying conventional control chart techniques is that the process data must be independently and identically distributed (Montgomery, 2009). This assumption is always violated in practice due to the existence of autocorrelation in the process data. Autocorrelation refers to the correlation of a variable with itself over successive time intervals. Autocorrelation may compromise the

performance of the control chart especially leading to too many false alarms (Alwan and Roberts, 1988; Maragah and Woodall, 1992, Thaga 2008). For example, Thaga (2008) suggested that positive autocorrelation of the process variables can result in severe negative bias in traditional estimators of the standard deviation. This bias produces control limits that are much tighter than desired and as a result more false alarms are generated. Lu and Reynolds (1999) also observed that autocorrelation in the monitored data can result in a higher false alarm rate than expected. Given the adverse effects of autocorrelation on the performance of the statistical process control chart, there is a need to take into consideration autocorrelation when designing the statistical process control chart.

4.2.3 Time series based control chart

Many practical solutions have been provided to eliminate the effects of autocorrelation and nonstationarity for the control chart (Wheeler, 1991; Box and Kramer, 1992; MacGregor, 1987, 1990; Montgomery, 2009). One commonly used solution is modeling the data through an appropriate time series model and estimating residuals from the model (Alwan and Roberts, 1988). The autoregressive-integrated-moving average (ARIMA) model is one of the time series models that can be applied for modeling and forecasting the non-stationary time series data (Alwan and Roberts, 1988; Haridy and Wu, 2009).

In time series analysis, the autoregressive model and moving average model are commonly used. The ARIMA model is an integration of both the autoregressive and moving average models. In the autoregressive model, one specific observation in a time

series is dependent on previous observations. In other words, the observation at time t (x_t) can be regressed on its past consecutive values plus an error (also known as random shock) (e_t) as in Eq. 4.1.

$$x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \dots + e_t \quad (4.1)$$

or equivalently as:

$$(1 - \sum_{j=1}^{\infty} \Phi_j B^j) x_t = e_t \quad (4.2)$$

where Φ_j is the autoregressive parameter and B^j is known as the backshift operator that is defined as:

$$B^j x_t = x_{t-j} \quad (4.3)$$

The moving average model, on the other hand, suggests that each observation in the time series can be affected by the past random shock (i.e. error) that cannot be accounted for by the autoregressive component. In the moving average model, each observation in the time series can be represented as a linear combination of errors and a constant (μ) as:

$$x_t = \mu + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \dots \quad (4.4)$$

or equivalently as:

$$x_t - \mu = (\sum_{j=1}^{\infty} \theta_j B^j) e_t \quad (4.5)$$

where θ_j is the moving average parameter.

The ARIMA model can be used to model the autocorrelation in original data set and generate the non-autocorrelated residuals in an output data set by applying an initial “differencing” step. The conventional statistical process control chart (e.g. Shewhart control chart) can then be developed based on these residuals.

4.3 Fall detection model

4.3.1 Overview

In the proposed fall detection model, the statistical process control chart is used to monitor the real-time fall indicator time series and detect the occurrence of falls. The statistical process control chart is based on the ARIMA model and constructed following three steps: 1) autocorrelation assessment, 2) ARIMA modeling, and 3) control chart construction (Figure 4-1). In particular, the autocorrelation coefficient function (ACF) is used to assess the autocorrelation in the fall indicator time series in the first step. If the autocorrelation is not found, we directly go to Step 3 to construct the control chart using the original time series of fall indicators. Otherwise, an ARIMA model is used to eliminate the autocorrelation in Step 2. The time series of fitted residuals are then used to specify the control chart in Step 3. Details of these steps are presented in the following sections.

Figure 4-1 Flow chart of the fall detection model development

4.3.2 Step 1: Autocorrelation assessment

The autocorrelation in the selected fall indicator time series is assessed by the ACF plot. The ACF plot (aka. correlogram) is the plot of the autocorrelation coefficients versus the time lags. The autocorrelation coefficient at lag k measures the correlation between one time series and the same time series lagged by k time units. In this study, the autocorrelation coefficient was calculated by the ‘autocorr’ function from the MATLAB™ econometric toolbox (The MathWorks, Natick, MA, USA).

The autocorrelation is asserted if the ACF plot demonstrates a “tail off” pattern (i.e. the value of ACF decreases gradually) (Montgomery et al., 2008). Specifically, according

to Nau (2005), the ‘tail off’ pattern is identified if the ACF at Lag 10 is significantly larger than zero at the confidence of 0.95.

4.3.3 Step 2: ARIMA modeling

If the autocorrelation of fall indicator time series is asserted in Step 1, an appropriate ARIMA model should be found for each autocorrelated fall indicator time series to eliminate the autocorrelation. The ARIMA model can be generalized as an ARIMA (p, d, q) model, where p, d, and q are integers ≥ 0 and represent the orders of the autoregressive, differencing and moving average parts of the model, respectively. Given the ARIMA (p, d, q) model, the original time series x_t can be fitted and converted into non-autocorrelated residual time series (i.e. e_t). The relationship between the original time series x_t and fitted residual time series e_t can be expressed as follows:

$$(1 - \sum_{p=1}^p \phi_p B^p)(1 - B)^d x_t = (1 + \sum_{q=1}^q \theta_q B^q) e_t \quad (4.6)$$

where ϕ_p and θ_q represent the autoregressive parameter and the moving average parameter, respectively (i.e. the parameters of autoregressive and moving average parts of ARIMA model); B is the backshift operator (Eq. 4.3).

The ARIMA modeling follows a three-step iterative procedure: model identification, parameter estimation, and diagnosis check (Box and Jenkins, 1976). Model identification is used to specify the values of p, d, and q. Then, the unknown parameters of the model (i.e. the value ϕ_p and θ_q) are estimated. Finally, the diagnosis check is performed to determine the adequacy of the model.

4.3.3.1 Model identification

In model identification, the first step is to convert the fall indicator time series data into stationary data by using successive differencing. The first and second order differencing operations on the original time series can be expressed by Equation 4.7 and 4.8, respectively (Montgomery et al., 2008):

$$(1 - B)x_t = x_t - x_{t-1} \quad (4.7)$$

$$(1 - B)^2 x_t = (1 - 2B + B^2)x_t = x_t - 2x_{t-1} + x_{t-2} \quad (4.8)$$

The ACF and partial autocorrelation function (PACF) are then plotted for the differenced time series with various differencing orders, respectively. The differencing order (i.e. d) selected for the ARIMA model is the least one whose corresponding ACF and PACF plots show the similar patterns with any of the theoretical patterns provided by Montgomery et al. (2008) (Table 4.1). More specifically, ACF tailed off and the PACF cut off at lag p suggest using an ARIMA ($p, d, 0$) model (i.e. a p -th order autoregressive model); ACF cut off at lag q and the PACF tailed off suggest an ARIMA ($0, d, q$) model (i.e. a q -th order moving-average model); if both ACF and PACF tailed off, a model with a mix of autoregressive and moving average parts (i.e. ARIMA(p, d, q), $p \neq 0$ and $q \neq 0$) should be used. If the identified ARIMA model is the mixed autoregressive and moving-average model, four tentative mixed autoregressive and moving-average models are selected, i.e. ARIMA (1, d , 1), ARIMA (1, d , 2), ARIMA (2, d , 1) and ARIMA (2, d , 2). Most time series in practice can be adequately modeled by an ARIMA (p, d, q) model with p, d and $q \leq 2$ (Montgomery et al., 2008).

Table 4.1 ARIMA models and the corresponding theoretical ACF and PACF patterns. Tails off means that the ACF decays in an exponential, sinusoidal or geometric fashion with a relatively large number of nonzero values. Cuts off means that function truncates abruptly with only a very few nonzero values.

Model	ACF	PACF
ARIMA(p, d, 0)	Tails off	Cuts off after lag p
ARIMA (0, d, q)	Cuts off after lag q	Tails off
ARIMA (p, d, q)	Tails off	Tails off

4.3.3.2 Parameter estimation

After the model identification, parameter estimation is carried out to estimate the parameters (i.e. the value of ϕ_p , θ_q and e_t) in the identified ARIMA model using the maximum likelihood estimation method. More specifically, these parameters are estimated by maximizing the conditional log likelihood function which can be written as:

$$l_*(\phi_p, \theta_q, \sigma_{e_t}^2) = -\frac{n}{2} \ln(\sigma_{e_t}^2) - \frac{S_*(\phi_p, \theta_q)}{2\sigma_{e_t}^2} \quad (4.9)$$

where $\sigma_{e_t}^2$ is the variance of e_t ; $S_*(\phi_p, \theta_q)$ is the sum of e_t^2 and estimated as follows:

$$S_*(\phi_p, \theta_q) = \sum_{t=1}^n e_t^2 (\phi_p, \theta_q | (1-B)x_{t*}, e_{t*}, (1-B)x_t) \quad (4.10)$$

Among the four tentative models in the case of mixed autoregressive and moving-average model (i.e. ARIMA (p, d, q), $p \neq 0$ and $q \neq 0$), the most appropriate one is that with the lowest Akaike information criterion (AIC). The AIC is a measure of the relative goodness of fit of a statistical model. A smaller AIC indicates a better model estimation (Akaike, 1974). The MATLAB™ econometric toolbox (The MathWorks, Natick, MA, USA) was used for parameter estimation and calculation of AIC in this

study. For more detailed information regarding the parameter estimation and model selection by AIC, the readers can refer to Box and Jenkins (1976) and Akaike (1974).

4.3.3.3 *Diagnosis check*

After specifying the model parameters, the diagnosis check is carried out to assess whether the autocorrelation of the original kinematic measures has been eliminated adequately. This is done by analyzing the ACF of the residuals (e_t). Autocorrelation is considered to be removed if the ACF of the residuals does not differ significantly from zero for all lags greater than ten (Nau, 2005). Otherwise, the ARIMA modeling procedure is repeated until no autocorrelation is found.

4.3.4 Step 3: Control chart construction

‘Historical’ fall indicator data during non-fall activities are used to establish the Shewhart individuals control chart for fall detection by specifying the individual-specific control limits (CLs) based on the Shewhart three sigma control theory (Shewhart, 1931). The ‘historical’ data are either the original time series (x_t) or the residual time series obtained from the ARIMA model (e_t), depending on whether x_t is autocorrelated or not. Let a_i represents the selected ‘historical’ fall indicator data at time point i . The CLs are determined as follows:

$$CL_{(Upper|Lower)} = \bar{X} \pm 3sigma = \bar{X} \pm 3 \frac{\overline{mr}}{d_2} \quad (4.11)$$

where $\bar{X} = \frac{\sum_{i=1}^T a_i}{T}$ and T are the mean value and the duration of the ‘historical’ fall indicator time series, respectively. The process standard error (i.e. sigma) is estimated by the mean

moving range ($\overline{mr}$) divided by the sample-size-specific constant d_n , where n is the sample size for estimating the standard error. In the Shewhart individuals control chart, the moving range of two successive values in the time series (Shewhart, 1931) is used for the estimation of the process variability. Therefore, the sample size here is $n=2$. The value of $d_2 = 1.128$ is obtained from Montgomery (2009). The moving ranges are defined by the magnitudes of the differences between successive data points which can be written as $mr_i = |a_i - a_{i-1}|$. Subsequently, $\overline{mr}$ is determined as $\overline{mr} = \frac{\sum_{i=2}^T mr_i}{T-1}$.

4.4 Model application

4.4.1 Fall indicator selection

To develop an effective fall detection model, the first critical issue is the selection of appropriate fall indicators. In Chapter 3, we found that head vertical acceleration, upper arm vertical velocity, trunk vertical velocity, shank frontal velocity, and head frontal angular velocity were able to effectively and efficiently distinguish falls from non-fall activities. Thus, these kinematic measures were selected as the fall indicators in the present study.

4.4.2 Experiment

Sixty young participants were involved in this study (30 male and 30 female, age 24.2 ± 2.1 years; height 169.1 ± 9.2 cm; weight 58.5 ± 10.3 kg). They self-reported to be free of any medical conditions that may affect their gait patterns. All participants signed an informed consent form approved by the NTU Institutional Review Board.

Apparatus and experimental protocol were the same with those in Chapter 3. In brief, the participants were instructed to walk on a 12-meter-long linear platform at their self-selected speed. Slips were induced unexpectedly in terms of the slipping location and time using a movable vinyl tile sheet covered by detergent. There were four normal walking trials and four slip trials presented to each participant in a random order. Body kinematic data during walking on the platform were collected using an eight-camera motion capture system (Motion Analysis Eagle System, Santa Rosa, CA, USA).

4.4.3 Data selection

In total, there were 233 slip trials and 240 normal walking trials obtained from the experiment. The unbalanced number was due to that some participants did not strike on the slippery surface and/or marker missing during slips. In the slip trials, there were 120 successful balance recovery and 113 failed balance recovery (i.e. falls). The experimental trials from each participant were classified into two random subsets: training subset and testing subset. The training subset for each participant included one normal walking trial and one successful recovery trial and was used to specify the individual-specific fall detection model as described in Section 4.3. The rest experimental trials belonged to the testing subset and were used for the model evaluation purpose. Fall indicator time series data from at least two complete gait cycles in the normal walking trial were used for model specification and evaluation. For slip trials, the fall indicator time series data under analysis started from at least one complete gait cycle prior to slip occurrence till slip recovery (i.e. marked as the end of the unilateral slip) or fall completion (i.e. when the body was completely supported by the harness).

4.4.4 Evaluation

The constructed fall detection models were used to monitor fall indicator time series. If the fall indicator went beyond either the upper or lower control limit, a fall was considered to be detected. Otherwise, the activity was classified to be a non-fall activity. Figure 4-2 illustrates an example of using the proposed fall detection model to monitor the time series of one fall indicator (i.e. head vertical acceleration) in different experimental trials. The source of the data was randomly selected from one of the participants. The control chart was constructed by following model development steps described in Section 4.3, and was evaluated for three conditions: normal walking, successful recovery and falls.

In this example, a fall due to slips was successfully detected 820ms after heel contact over the slippery surface, and the time series of the selected non-fall trials were all within the area defined by the upper and lower control limits.

Figure 4-2 An example of using the proposed model to monitor various activities

The fall detection model was evaluated using the measures of sensitivity, specificity and detection time. Sensitivity was defined by the ratio of the number of successfully detected falls over total number of falls. Specificity was the ratio of the number of successfully detected non-fall activities over the total number of non-fall activities (Noury et al. 2008). Detection time is the time difference between time point when the heel of slipping foot struck the slippery surface and fall detection. This variable was used to indicate how rapid the fall detection system responds to a fall. A better fall detection performance was associated with a smaller detection time, larger sensitivity, and larger specificity.

4.5 Results

The autocorrelation assessment results revealed that all the fall indicator time series were autocorrelated. After ARIMA modeling, non-autocorrelated fitted residuals were obtained for all the fall indicator time series. Figure 4-3 illustrated the results of one of the fall indicators from the autocorrelation assessment and ARIMA modeling for one participant. In particular, Figure 4-3a showed the original time series. Figure 4-3b showed that the ACF plot did not cutoff at Lag 10 indicating that this fall indicator time series were autocorrelated. Differenced time series were then determined (e.g. Figure 4-3c). It was found that the ACF plot (Figure 4-3d) and PACF plot (Figure 4-3e) for the first order differenced time series had “tail off” pattern and cut off pattern after Lag 2, respectively. This indicated that an ARIMA (2, 1, 0) should be appropriate. A residual time series (Figure 4-3f) was then obtained. The diagnosis check revealed that the residual time series were not autocorrelated, since the autocorrelation coefficient decay rapidly to the value that was not significantly larger than zero at Lag10 (Figure 4-3g).

Figure 4-3 a) Typical time series of a fall indicator (normal gait); b) ACF of the corresponding original time series; c) First order differenced time series; d) ACF of the differenced time series; e) PACF of the differenced time series; f) Residual time series obtained from ARIMA model; g) ACF of residual time series. The dash line indicates the 95% confidence interval within which ACF is not significantly different from zero.

The individual-specific control limits for each fall indicator were presented in Table 4.2. The results from model evaluation were given in Table 4.3. Except for the sensitivity obtained from shank frontal velocity, the sensitivity and specificity for all the fall indicators were larger than 90%. In particular, trunk vertical velocity was associated with the highest sensitivity (i.e. 94.7%). Shank frontal velocity was associated with the highest specificity (i.e. 99.2%). When comparing the detection time among the fall indicators, trunk vertical velocity was associated with the least mean detection time (i.e. 620ms).

**Table 4.2 The individual-specific control limits for each fall indicator
(participant 1-30)**

Fall indicator	Head acceleration	vertical	Upper arm vertical velocity	Trunk vertical velocity	vertical	Shank velocity	frontal	Head angular velocity	frontal	
Participant	UCL	LCL	UCL	LCL	UCL	LCL	UCL	LCL	UCL	LCL
1	0.064	-0.064	0.136	-0.136	0.297	-0.293	0.156	-0.152	0.141	-0.143
2	0.290	0.0290	0.150	-0.157	0.345	-0.364	0.063	-0.059	0.177	-0.184
3	0.038	-0.039	0.169	-0.172	0.368	-0.370	0.207	-0.202	0.016	-0.016
4	0.073	-0.071	0.041	-0.040	0.092	-0.089	0.138	-0.135	0.020	-0.019
5	0.033	-0.035	0.085	-0.083	0.223	-0.222	0.479	-0.453	0.027	-0.027
6	0.020	-0.020	0.084	-0.088	0.295	-0.304	0.243	-0.246	0.154	-0.152
7	0.206	-0.206	0.053	-0.054	0.141	-0.141	0.110	-0.123	0.054	-0.058
8	0.055	-0.056	0.056	-0.057	0.127	-0.134	0.092	-0.097	0.132	-0.105
9	0.048	-0.048	0.055	-0.053	0.090	-0.087	0.132	-0.126	0.151	-0.164
10	0.033	-0.034	0.042	-0.042	0.074	-0.075	0.117	-0.117	0.163	-0.161
11	0.115	-0.118	0.111	-0.111	0.114	-0.112	0.015	-0.016	0.143	-0.137
12	0.079	-0.078	0.194	-0.194	0.093	-0.093	0.233	-0.230	0.148	-0.151
13	0.102	-0.103	0.088	-0.089	0.114	-0.108	0.036	-0.037	0.132	-0.148
14	0.111	-0.107	0.589	-0.593	0.301	-0.320	0.185	-0.169	0.031	-0.033
15	0.067	-0.067	0.072	-0.075	0.250	-0.255	0.152	-0.136	0.064	-0.059
16	0.072	-0.072	0.194	-0.198	0.248	-0.246	0.064	-0.062	0.090	-0.086
17	0.142	-0.141	0.088	-0.091	0.203	-0.195	0.190	-0.194	0.179	-0.177
18	0.059	-0.058	0.072	-0.072	0.139	-0.136	0.209	-0.184	0.099	-0.085
19	0.109	-0.109	0.156	-0.157	0.128	-0.129	0.312	-0.316	0.120	-0.098
20	0.028	-0.028	0.064	-0.064	0.087	-0.089	0.201	-0.164	0.091	-0.070
21	0.165	-0.166	0.042	-0.042	0.082	-0.083	0.106	-0.094	0.021	-0.024
22	0.062	-0.062	0.103	-0.103	0.218	-0.218	0.118	-0.123	0.092	-0.089
23	0.204	-0.204	0.035	-0.035	0.059	-0.058	0.109	-0.094	0.062	-0.052
24	0.234	-0.231	0.028	-0.028	0.057	-0.058	0.055	-0.049	0.063	-0.060
25	0.162	-0.164	0.033	-0.032	0.066	-0.066	0.083	-0.085	0.026	-0.031
26	0.105	-0.102	0.034	-0.034	0.053	-0.053	0.101	-0.113	0.073	-0.079
27	0.058	-0.059	0.029	-0.029	0.048	-0.048	0.067	-0.074	0.073	-0.068
28	0.049	-0.048	0.028	-0.028	0.060	-0.059	0.131	-0.123	0.140	-0.120
29	0.246	-0.247	0.040	-0.040	0.079	-0.078	0.125	-0.134	0.010	-0.010
30	0.053	-0.052	0.020	-0.020	0.034	-0.034	0.115	-0.115	0.041	-0.042

**Table 4.2 The individual-specific control limits for each fall indicator
(continued participant 31-60)**

Fall indicator	Head acceleration	vertical	Upper arm vertical velocity	Trunk vertical velocity	vertical	Shank vertical velocity	frontal	Head angular velocity	frontal	
Participant	UCL	LCL	UCL	LCL	UCL	LCL	UCL	LCL	UCL	LCL
31	0.083	-0.083	0.052	-0.053	0.112	-0.111	0.856	-0.808	0.045	-0.046
32	0.110	-0.104	0.023	-0.023	0.037	-0.037	0.103	-0.099	0.054	-0.059
33	0.145	-0.142	0.026	-0.026	0.042	-0.042	0.135	-0.137	0.043	-0.046
34	0.120	-0.121	0.029	-0.029	0.050	-0.050	0.098	-0.091	0.044	-0.043
35	0.085	-0.085	0.134	-0.134	0.225	-0.224	0.036	-0.036	0.045	-0.048
36	0.231	-0.231	0.089	-0.095	0.458	-0.455	0.164	-0.147	0.014	-0.013
37	0.165	-0.165	0.123	-0.123	0.175	-0.182	0.182	-0.146	0.018	-0.017
38	0.081	-0.081	0.153	-0.153	0.194	-0.182	0.031	-0.028	0.032	-0.034
39	0.085	-0.085	0.030	-0.030	0.059	-0.059	0.053	-0.049	0.067	-0.062
40	0.152	-0.162	0.019	-0.019	0.045	-0.045	0.114	-0.131	0.039	-0.041
41	0.109	-0.113	0.102	-0.102	0.134	-0.140	0.188	-0.213	0.058	-0.048
42	0.161	-0.161	0.138	-0.141	0.311	-0.292	0.082	-0.085	0.040	-0.041
43	0.151	-0.151	0.114	-0.114	0.606	-0.620	0.239	-0.230	0.033	-0.033
44	0.133	-0.137	0.040	-0.042	0.111	-0.116	0.115	-0.120	0.032	-0.032
45	0.174	-0.172	0.034	-0.034	0.066	-0.065	0.317	-0.257	0.357	-0.364
46	0.184	-0.182	0.179	-0.176	0.208	-0.210	0.088	-0.088	0.057	-0.060
47	0.122	-0.122	0.066	-0.065	0.153	-0.160	0.102	-0.072	0.039	-0.037
48	0.121	-0.121	0.208	-0.213	0.409	-0.413	0.203	-0.203	0.028	-0.028
49	0.102	-0.103	0.047	-0.048	0.103	-0.105	0.060	-0.062	0.023	-0.025
50	0.053	-0.053	0.199	-0.199	0.225	-0.226	0.177	-0.155	0.014	-0.017
51	0.334	-0.334	0.021	-0.021	0.070	-0.068	0.225	-0.240	0.019	-0.016
52	0.082	-0.083	0.024	-0.024	0.054	-0.055	0.222	-0.221	0.043	-0.042
53	0.187	-0.188	0.022	-0.022	0.041	-0.041	0.121	-0.084	0.065	-0.065
54	0.290	-0.292	0.056	-0.053	0.047	-0.047	0.232	-0.205	0.180	-0.168
55	0.240	-0.240	0.021	-0.021	0.033	-0.033	0.257	-0.272	0.057	-0.057
56	0.182	-0.184	0.023	-0.023	0.044	-0.044	0.096	-0.096	0.320	-0.331
57	0.024	-0.024	0.143	-0.134	0.253	-0.252	0.980	-0.964	0.076	-0.079
58	0.051	-0.051	0.022	-0.022	0.040	-0.040	0.171	-0.160	0.036	-0.034
59	0.145	-0.145	0.092	-0.087	0.229	-0.241	0.129	-0.138	0.063	-0.057
60	0.074	-0.076	0.035	-0.035	0.080	-0.083	0.451	-0.425	0.023	-0.023

Table 4.3 The model evaluation results

Fall indicator	Sensitivity	Specificity	Minimum detection time	Maximum detection time	Mean detection time
Head vertical acceleration	90.3% (102/113)	96.3% (231/240)	540ms	1010ms	630 ms
Upper arm vertical velocity	92.0% (104/113)	92.9% (223/240)	480ms	1000ms	710ms
Trunk vertical velocity	94.7% (107/113)	96.7% (232/240)	550ms	960ms	620ms
Shank frontal velocity	88.5% (100/113)	99.2% (238/240)	670ms	980ms	750ms
Head frontal angular velocity	91.2% (103/113)	95.4% (229/240)	560ms	900ms	680ms

4.6 Discussion

A novel pre-impact fall detection method based on the statistical process control chart was developed and evaluated in this study. The statistical process control chart is used to monitor real-time fall indicators and to detect their abrupt changes during the pre-impact phase of a fall. Detecting falls prior to the body impact onto the ground may facilitate the launch of protection devices (e.g. such as airbag) so as to avoid the injury caused by the impact (Tamura et al., 2009).

The highest sensitivity and specificity achieved by a single fall indicator in this study were 94.7% (by trunk vertical velocity) and 99.2% (by shank frontal velocity), respectively. These results were superior to those from previous studies that evaluated fall detection performance using realistic falls (Bagala et al., 2012; Doukas and Maglogiannis, 2010; Li et al., 2009). For example, Li et al. (2009) reported 91% sensitivity and 92% specificity, and the sensitivity and specificity reported by Doukas and Maglogiannis (2010) were about 90% and 85%, respectively.

Better fall detection performance was reported previously. In Bourke et al. (2008), for instance, 100% sensitivity and 97.5% specificity were obtained. Nyan et al. (2008a) reported 95.2% sensitivity and 100% specificity. In an extreme case, Wu and Xue

(2008)'s fall detection model did not lead to any miss or false alarm (i.e. sensitivity = 100% and specificity = 100%). However, a problem with these studies is that the data used for fall detection evaluation were from voluntary falls. In the real life, unexpected falls are involuntary in nature. A recent research revealed that fall detection algorithms that were successful at detecting voluntary falls may not perform well when attempting to detect realistic falls (Bagala et al., 2012). In addition, few fall detection studies included fall-like activities (e.g. successful recovery) for evaluation. Fall-like activities belong to non-fall activities, and thus should be differentiated from falls as well as other non-fall activities. Due to these facts, the external validity of the fall detection models from the above-mentioned previous studies is questionable. Unlike previous work, our fall detection model evaluation was based on the involuntary falls that are quite similar to those in real life. In addition, a fall-like activity (i.e. successful recovery) was included in both model development and evaluation. Therefore, the external validity of our proposed fall detection model can be guaranteed. Further, since fall-like activities share similar kinematic characteristics with falls, inclusion of fall-like activities would definitely lead to lower specificity. This can explain why the specificity of our model was relatively lower than that from some previous work (Nyan et al., 2008a).

In our experimental study (Section 4.4.2), four slip trials were presented to each participant. There are adapted gait changes to repeated slip exposures (Heiden et al., 2006). However, when developing and evaluating a fall detection model, all the activities can be simply classified into two groups: falls versus non-falls. What matters to a fall detection model is that a real fall cannot be missed and a non-fall activity cannot generate a false alarm. It does not matter whether the gait patterns are affected by some external

factors such as repeated slip exposures or not. Therefore, we believe that repeated exposures do not affect model development and evaluation in the present study.

Using the proposed fall detection model, falls can be typically detected around 600-700 ms after heel contact on the slippery surface. According to Beschoner et al. (2012) and Noury et al. (2008), the time interval between heel contact and fall impact can be estimated to be around 900ms. This indicates that the lead time obtained by our fall detection model is about 200-300ms. Wu and Xue (2008) suggested that triggering an instant protection device such as an airbag may only take 25ms. Therefore, our model can provide sufficient time for triggering fall protection device in the pre-impact phase, and thus potentially effective in preventing fall injuries.

Our model is superior to previous fall detection models mainly in two aspects. First, the fall indicators were selected based on experimental findings. The selection of fall indicators plays an important role in pre-impact fall detection (Noury et al., 2008). In previous fall detection models (Hwang et al., 2004; Mathie et al., 2004; Noury et al., 2000; Nyan et al., 2008a; Prado, 2002; Wu and Xue, 2008), the fall indicators were always chosen empirically without any experimental basis, which would compromise the validity of the model. Second, great variability exists in human motion patterns. To account for such variability, the fall detection model must be individual-specific. Our model is individual-specific. In particular, the control limits in the control chart were determined statistically based on each individual's historical data. Practically, this only requires each individual to perform a series non-fall activities to help construct the control limits.

The statistical process control chart has been demonstrated to be an effective tool in detecting any abnormal changes in a “controlled” process (Haridy and Wu, 2009). Falls are ‘uncontrollable’ and can be classified as being ‘abnormal’ when comparing with non-fall activities. Therefore, we proposed using the statistical process control chart to detect such an ‘abnormal’ event. The control limits were the key parameters in the statistical process control chart. In the present study, they were determined statistically according to the Shewhart’s three sigma control theory. Enormous amount of research has demonstrated the effectiveness of control charts in terms of detecting abnormality in the field of manufacturing, economy and healthcare (Haridy and Wu, 2009; Hayati et al., 2006; Woodall et al., 2004). The reason to choose the Shewhart individual chart among other control charts is that unlike other control charts which rely on data from subgroups, the Shewhart individual chart monitors each single observation which is suitable for our application. Besides, with the autocorrelation being removed by ARIMA modeling, the three sigma control limits could provide sufficient power to detect any abnormal changes from an under-controlled process without sounding frequent false alarms (Shewhart, 1933). Another attractive feature of using the control chart is that it can generate the out-of-control alert as soon as the data is out of control limits which may make fast fall detection possible.

This study only focused on detecting slip-induced falls during locomotion. There are other types of falls which are not covered in this study. Nevertheless, falls always consist of sudden movement of body during the pre-impact phase (Noury et al., 2008). The proposed model demonstrates the capacity to detect abrupt changes in body kinematics during falls. Therefore, it should be effective for detecting other types of falls.

Another limitation in the study is that only a limited number of activities were used in model development and evaluation. Though the normal locomotion and successful recovery from slips were believed to be representative of the normal activities and fall-like activities, respectively, future work may include more activities of daily living to construct the individual-specific control limits and evaluate the proposed fall detection model.

In summary, this chapter developed and evaluated a novel fall detection model based on the statistical process control chart. The model is individual specific and shows high detection accuracy in terms of specificity and sensitivity, and reasonable detection time. Though there is still a long way to go before integrating this model into the autonomous fall detection sensor and implementing it into the real life, the proposed method is promising in terms of developing a desirable fall detection solution.

Chapter 5 Detecting Falls Using A Fall Indicator Defined by A Linear Combination of Kinematic Measures

Abstract

The objective of this chapter was to determine whether a novel fall detection model based on the statistical process control chart performed better when the fall indicator was defined by a linear combination of multiple kinematic measures. To specify the fall indicator, an optimization procedure was performed in which the trial and error method was used to determine the relative weightings of selected kinematic measures that were associated with the optimal fall detection performance. The highest sensitivity, highest specificity, and lowest sum of squared errors of the fall detection model obtained from this study were 97.3%, 99.2% and 0.00133 respectively. These findings suggested that using the fall indicator defined by a linear combination of kinematic measures can lead to improved fall detection performance compared to that defined by a single kinematic measure.

5.1 Introduction

Kinematic measures have been widely used to define the fall indicator in the existing fall detection models. Advantages of using kinematic measures to define the fall indicator are twofold. First, kinematic measures can reflect changes of body dynamics due to falls in a real-time manner. Second, body kinematic measures can be monitored by wearable inertial sensors which make long-term tracking of fall risks technically feasible.

Some fall detection models used a single kinematic measure as the fall indicator (Rougier and Meunier, 2007; Wu and Xue 2008). For example, in Wu and Xue (2008), a fall was considered to occur if the trunk vertical velocity exceeded a pre-determined threshold. A single kinematic measure may not sufficiently account for falling dynamics. Therefore, in order to increase fall detection performance, many researchers used multiple kinematic measures to detect falls. In Wu (2000), for instance, a fall was detected if both the vertical and horizontal trunk velocity exceeded 1 m/s. More recently, Jacob et al. (2011) have used the gravitational force, the angular velocity and the angular acceleration at lower back to detect the occurrence of falls. In their model, falls were considered to occur if the acceleration measures exceeded 2.73g, angular velocity measures exceeded 2.74 rad/s, and angular acceleration measures were over 0.04 rad/sec² at the same time. In these studies, ‘AND’ logic was commonly used to combine various kinematic measures when defining the ‘fall’ condition. In other words, a fall was considered to occur only when the selected kinematic measures all satisfied the pre-defined criteria simultaneously. As a result, the existing fall detection models that used multiple kinematic measures to define the fall indicator have to report miss detection on a more frequent basis (i.e. decreased sensitivity).

Chapter 4 introduced a novel fall detection model based on the statistical process control chart. This model was superior to previous fall detection models mainly in two aspects. First, the fall indicators in this fall detection model were selected based on experimental findings, which improved the validity of this model. Second, this fall model was individual-specific, which can account for the variability of human motion patterns. In Chapter 4, the performance of the proposed fall detection model was examined separately for each selected kinematic measure. As multiple kinematic measures contain more information regarding falling dynamics compared to a single kinematic measure, we aimed to examine the performance of our proposed fall detection model using a fall indicator defined by a linear combination of multiple kinematic measures in this chapter. An optimization procedure was performed to specify the combination of the selected kinematic measures that was associated with the optimal fall detection performance.

5.2 Methods

5.2.1 The fall detection model

Based on the findings from Chapter 3, five kinematic measures were selected as the fall indicator candidates for the fall detection model. In Chapter 4, the fall detection model was developed based on the statistical process control chart. It was developed in three steps. Briefly, in step 1, the autocorrelation coefficient function (ACF) was used to assess the autocorrelation in the fall indicator time series. If the autocorrelation was not found, we directly went to step 3 to construct the control chart using the original time series of fall indicators. Otherwise, in step 2, an autoregressive integrated moving average (ARIMA) model was used to eliminate the autocorrelation by generating non-

autocorrelated time series (i.e. fitted residuals). In step 3, the fitted residuals were used to specify the control limits of a Shewhart individuals control chart which was used for detecting the abnormal changes of body dynamics due to falls. After the model construction, the model was used to monitor the fall indicator in real time. If the fall indicator went beyond either the upper or lower control limit, a fall was considered to be detected. Otherwise, the activity was classified to be a non-fall activity. Details of the proposed fall detection model were presented in Chapter 4.

5.2.2 Definition of the fall indicator

In Chapter 4, the highest sensitivity (i.e. 94.7%) and highest specificity (i.e. 99.2%) were obtained by using the fall indicators defined by trunk vertical velocity and shank frontal velocity, respectively. Therefore, in this chapter, the fall indicator was defined by a linear combination of the trunk vertical velocity and shank frontal velocity as follows:

$$Fall\ indicator = xTVV_t + (1 - x)SFV_t \quad (5.1)$$

where TVV_t represented the trunk vertical velocity, SFV_t represented the shank frontal velocity, and x was a weighting factor and within the range of $[0, 1]$. In order to specify the value of x that was associated with the optimal fall detection performance, an optimization procedure was performed whose objective function was defined to minimize the sum of squared errors of the fall detection model defined as follows:

$$\text{sum of squared errors} = (\text{type I error})^2 + (\text{type II error})^2 \quad (5.2)$$

where type I error = 1-specificity and type II error = 1-sensitivity. In the optimization procedure, the trial and error method was used. In particular, x was set at various values with an equal interval of 0.01 within its specified range (i.e. $x = 0, 0.01, 0.02, 0.03, \dots$,

0.98, 0.99, and 1). Using the fall detection model developed in Chapter 4, the sum of squared errors corresponding to each x value was calculated. The optimal x was identified as that associated with the minimum sum of squared errors.

5.2.3 Data selection

The data used for model development and evaluation were from the Chapter 4. In total, there were 233 slip trials and 240 normal walking trials obtained from the experiment. Among the slip trials, there were 120 successful balance recovery and 113 failed balance recovery (i.e. falls). The experimental trials from each participant were classified into two random subsets: training subset and testing subset. The training subset for each participant included one normal walking trial and one successful recovery trial and was used to specify the individual-specific fall detection model as described in Chapter 4. The rest experimental trials (113 falls and 240 non-falls) belonged to the testing subset.

5.3 Results

Figure 5-1 illustrated how the sensitivity, specificity and sum of squared errors changed with the weighting factor x . The smallest value of sum of squared errors = 0.00133 (sensitivity= 97.3% and specificity= 97.5%) was found when the weighting factor x was between 0.25-0.29. Besides, the highest sensitivity (97.3%) and highest specificity (99.2%) were achieved when $x= 0.25-0.29$ and $x= 0.84-1$, respectively.

Figure 5-1 a) sensitivity, b) specificity, and c) sum of squared errors.

5.4 Discussion

In the earlier investigation (Chapter 4) that used a single kinematic measure to define the fall indicator, the highest sensitivity, highest specificity, and minimum value of sum of squared errors were 94.7%, 99.2% and 0.00390, respectively. As can be seen in Figure 5-1, with combined fall indicators, the corresponding values we obtained were 97.3%, 99.2% and 0.00133 for sensitivity, specificity, and sum of squared errors, respectively. Therefore, the fall detection model based on the statistical process control chart performed better when the fall indicator was defined by a linear combination of multiple kinematic measures. This finding is reasonable since more kinematic measures could better account for falling dynamics.

Some previous fall detection studies also used multiple kinematic measures to indicate the fall status (Nyan et al., 2008a; Jacob et al., 2011; Wu, 2000). However, these studies mainly used 'AND' logic to combine kinematic measures which would result in decreased sensitivity. The attempt to find the optimal combination of kinematic measures as one fall indicator was seldom seen. The difficulties were partially due to the waveform feature of the kinematic measures. Kinematic measures during gait, fall or other activities always appear as time-series. Each data point sampled at each time frame (i.e. at different percentage of gait cycle/stance) of such time-series waveform should be considered as one dimension (Deluzio and Astephen 2005). Therefore even one kinematic measure under repeated observation (taken from different activities) had very high dimensionality. If two or more kinematic measures were under consideration, the complexity of the data would be enormous. The traditional dimensionality reduction tool such as principal component analysis would not be capable for such application. To overcome this problem,

the fall indicator as a linear combination of kinematic measures was proposed in this chapter. The advantage of using the linear combination is that it is the simplest format of combination that makes the analysis and implementation easy. The improved fall detection performance have supported that linear combination is a wise choice to combine kinematic measures.

An optimization procedure was performed to specify the relative weightings of the selected kinematic measures. The trial and error method, which is a widely accepted heuristic method, was chosen in the optimization procedure because the optimization problem in the present study was a highly non-linear problem that can only be addressed by heuristic methods. In addition, the trial and error method was chosen because it is less computationally intensive compared to other heuristic methods such as genetic algorithms and simulated annealing.

The optimal weighting factor x was found to be within a range, not at a specific value. This is because of the limited amount of experimental data (i.e. 240 normal walking trials and 233 slip trials including 120 successful balance recovery and 113 falls) available for the model development and evaluation. Given that kinematic measures during activities of daily living are continuous in nature, the exact value of the optimal weighting factor x in an ideal condition (i.e. a condition with infinite amount of data for model development and evaluation) should be within the specified range (i.e. $x = 0.25$ - 0.29) by the present study. Thus, the optimal weighting range can be used to guide the specification of the linear combination in practical application of the proposed fall detection model.

The attempt to define new fall indicator by a linear combination of multiple kinematic measures is exploratory. Only two measures (trunk vertical velocity and shank frontal velocity) were selected to define the new fall indicator. It was difficult to provide theoretical justification about such selection, due to the complexity of possible combination of the kinematic measures (as discussed above, mainly resulted from their waveform features). Therefore the selection was made from a practical perspective where two measures were selected based on their relative high sensitivity and specificity compared with others. There was a possibility that other pairs could potentially provide better model performance. However since other measures had lower individual sensitivity and specificity, It was unlikely they can generate a better performance. This study only examined the linear combination of kinematic where an assumption was made that type I and Type II errors had equal “costs” (Equation 5.1). However, given that there were probably complex interrelationships (or correlations) among the kinematic measures, fall indicator can possibly be defined by non-linear combination of kinematic measures. Therefore, it might be of interest to study the performance of the fall detection model using the fall indicator defined by nonlinear combinations of kinematic measures in the future. However, this was much more challenging than the linear combination. First, traditional intercorrelation analysis method does not extend to time series curves like the kinematic measures. Complex mathematical derivations have been proposed (Chau 2001). However, to date, there is no generally census upon the proper method in this regards. Therefore it was difficult to assess the dependencies of the kinematic measures quantitatively. Without clearly justification of this correlation, we can only reveal that the

current approach generated a better fall indicator, but it was difficult to reveal it was the optimal one. Future work might need to apply advanced data analysis tool in this regards.

In summary, the findings from the present study suggest that using the fall indicator defined by a linear combination of kinematic measures can lead to improved fall detection performance compared to that defined by a single kinematic measure. This emphasizes the importance of selecting appropriate fall indicators for fall detection models. The optimization techniques used in this study approved to be able to provide a practical solution in the attempt to find a better fall indicator.

Chapter 6 Conclusion and Future Research

6.1 Conclusion and research contributions

A number of limitations in the existing fall detection research have been addressed. In particular, in order to address the problem that the development of existing fall detection models lacks experimental basis, an experimental study was conducted (Chapter 3) in which a comprehensive set of kinematic measures were examined in terms of their ability to differentiate slip-induced falls from non-fall activities. Appropriate fall indicators were identified based on the experimental findings. Thus, bias in the selection of fall detection indicators can be eliminated and internal validity of the proposed fall detection model can be guaranteed. The proposed fall detection model was based on the statistical process control chart, in which the fall detection parameters were specified based on individual's 'historical' movement data (Chapter 4). Thus, the proposed model is individual specific and able to address individual differences. Further, unlike previous studies, realist falls and near-fall activities were both involved in model development and evaluation. Therefore, findings with regard to the fall detection performance can be well generalized into the real life situations, and external validity of the proposed fall detection model can be guaranteed. Results from the fall detection evaluation have shown that this fall detection model is effective and efficient since it is associated with high detection specificity and sensitivity and sufficient detection time for triggering fall protection device in the pre-impact phase. Further, this dissertation appeared to be the first attempt to explore what could be the optimal fall indicators for fall detection (Chapter 5). In particular, the fall indicator defined by a linear combination of multiple kinematic

measures leads to improved fall detection performance compared to that defined by a single kinematic measure. This finding can help establish guidelines for the selection of optimal fall indicators in the fall detection research.

6.2 Limitations and future work

Only young participants were involved in this study. Elderly haven't been involved mainly due to safety and ethics concern. This is also a limitation faced by most the of fall related studies in which it is quite common that relevant data were collected from younger participants. Although age-related differences may exist, the slipping mechanisms are the same for both younger and older people. Therefore, the findings based on the data from younger people are still able to reveal the movement patterns of the older adults.

Three activities including normal walking, successful recovery from slips, and slip-induced falls were used to develop and evaluate the proposed fall detection model. Although these three activities were considered to be representative of ADLs, fall-like activities, and falls (as argued in earlier chapters), they cannot completely account for the body kinematic characteristics of various activities in real life. In the future work, the proposed fall detection model needs to be tested using the data from more ADLs (e.g. sit-to-stance, stance-to-sit, and stair negotiation) and different types of falls (e.g. trip-induced falls).

Another limitation of this research is that the proposed model was built and evaluated using the body kinematic data collected by the optical motion capture system in laboratory-based experiments. The optical motion capture system can provide accurate

body kinematic data. However, such equipment was extremely expensive and limited by capture volume. This prohibits the long-term tracking and monitoring of fall risks and makes the application of the proposed model in real life situations difficult. Inertial sensors have the features of low costs, small size, and power efficiency which makes long-term tracking and monitoring of fall risks possible. Actually, many researchers have used inertial sensors in human motion data collection. Future research could involve developing inertial-sensor-based fall detection device which integrates the proposed fall detection algorithm based the statistical process control chart.

In our attempt to determine the optimal fall indicator for fall detection (Chapter 5), we only tested the linear combination of kinematic measures. Thus, the findings from this attempt can only reveal better fall indicator, not the optimal one. In order to determine the optimal fall indicators, more complex combinations of kinematic measures (e.g. non-linear combinations) need to be examined with the proposed fall detection model in the future research.

In summary, future research could be done from three aspects. First, a wearable fall detection approach should be investigated. Inertial sensors could provide a feasible solution to wearable fall detection. Second, the fall detection model should be developed and evaluated by using the data from more ADLs and different types of falls. This could enhance the external validity of the proposed fall detection model. Third, the fall indicator plays an essential role in fall detection. Future research needs to address what is the possible optimal fall indicator. Besides these, to be effective, it is also important to specify how to protect fallers after detecting the occurrence of the fall. Airbag technology has been a mature technology nowadays and been widely used to prevent impact injuries

caused unexpected collisions, e.g., automobile collisions. Thus, it is of interest to study how to integrate fall detection technology with airbag technology in future research.

APPENDIX I: The definition of gait related terms

Gait cycle:	Starts when one foot makes contact with the ground and ends when that same foot contacts the ground again
Stance:	Starts when one foot makes contact with the ground and ends when the toe of foot leave the ground.
Slips:	The heel velocity failed to drop to zero upon the foot makes contact with the ground due to the low friction coefficient.
Falls:	Completed lost balance. In the experiment, it was identified if the midpoint between the left and right hip joint centers (estimated by the ASIS markers) dropped below 95% of its minimum height measured during normal walking.
Successful balance recovery:	Restore the balance without assistance after initial loss of balance. In the experiment, it was identified if the midpoint between the left and right hip joint centers dropped was not below 95% of its minimum height measured during normal walking.
Segment translational measures:	Linear velocities and linear accelerations of the segmental COM.
Segment linear velocities:	The rate of change of body segment centre of mass displacement.
Segment linear accelerations:	The rate of change of body segment centre of mass velocity.
Segment rotational measures:	Segment rotational velocities and segment rotational accelerations

Segment rotational velocities:	The rate of change of Euler angles accounting for the orientation of the corresponding segmental local frame with respect to the global reference frame.
Segment rotational accelerations:	The rate of change of segment rotational velocities.
Joint angular measures:	Joint angular velocities and joint angular accelerations
Joint angular velocities:	The rate of change of Euler angles accounting for the orientation of the corresponding segmental local frame with adjunct segmental local frame.
Joint angular acceleration:	The rate of change of joint angular velocities.
The moment of heel contact:	When the heel of the slip foot struck the slippery surface
The moment of recovery:	Marked at end of the unilateral slip
The moment of fall completion:	When the body was completely supported by the harness
Lead time:	The time interval between detecting the fall and the end of the fall.

APPENDIX II: The participants anthropometric data

Table A-1 Male participant

Participant Number	Age	Height (cm)	Weight (kg)
1	27	180	61
2	25	165	65
3	24	183	57
4	24	181	79
5	23	175	62
6	23	180	68
7	25	173	59
8	24	164	53
9	26	180	75
10	25	178	56
11	26	165	52
12	23	180	65
13	23	170	66
14	21	172	66
15	25	178	55
16	24	182	62
17	26	182	63
18	25	168	70
19	26	188	76
20	25	170	65
21	26	178	56
22	27	178	65
23	27	174	57
24	22	166	57
25	24	180	73
26	20	178	55
27	23	160	47
28	23	167	79
29	24	179	65
30	24	181	76
Mean	24.3	175.2	63.5
Standard deviation	1.7	6.9	8.4

Table A-2 Female participant

Participant Number	Age	Height (cm)	Weight (kg)
1	24	160	56
2	25	164	47
3	25	157	42
4	23	160	44
5	24	163	60
6	26	160	46
7	24	166	48
8	24	157	45
9	22	168	66
10	26	165	54
11	24	164	62
12	22	167	62
13	22	169	64
14	24	162	60
15	27	157	44
16	25	164	59
17	25	166	50
18	26	167	66
19	23	164	62
20	24	164	62
21	22	164	58
22	26	163	44
23	25	166	60
24	24	163	49
25	24	165	48
26	24	164	53
27	24	157	40
28	24	159	42
29	22	164	59
30	24	163	53
Mean	24.1	163.1	53.5
Standard deviation	1.3	3.3	8.1

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