Doctoral Thesis

Inertial Sensor Based Fall Risk Assessment and System Development for the Community-dwelling Older People

Hai Qiu

Department of Human and Systems Engineering

Graduate School of UNIST

2016

Inertial Sensor Based Fall Risk Assessment and System Development for the Community-dwelling Older People

Hai Qiu

Department of Human and Systems Engineering

Graduate School of UNIST

Inertial Sensor Based Fall Risk Assessment and System Development for the Community-dwelling Older People

A dissertation
submitted to the Graduate School of UNIST
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Hai Qiu

1. 18. 2016
Approved by

Advisor
Shuping Xiong

Inertial Sensor Based Fall Risk Assessment and System Development for the Community-dwelling Older People

Hai Qiu

This certifies that the dissertation of Hai Qiu is approved.

1. 18. 2016

Signature

Advisor: Prof. Shuping Xiong

Signature

Prof. Ravindra S. Goonetilleke

Signature

Prof. Gwanseob Shin

Signature

Prof. Oh-Sang Kwon

Signature

Prof. Sang Hoon Kang

Inertial Sensor Based Fall Risk Assessment and System Development for the Community-dwelling Older People

Hai Qiu

ABSTRACT

Along with the global trend of population ageing, falls present a substantial public health problem among elderly people over the age of 65. The objective of this research was to develop a low-cost, portable and inertial sensors based tool for assessing falls risk in the older people. To achieve this goal, three stages of studies have were conducted. The first stage aimed to design a test protocol based on the human balance system for assessing the risk of falling. The test protocol consisted of seven main tests, i.e., sensory integration test, limits of stability test, sit-to-stand five times test, timed up and go test, motor function test, reaction test, and short falls efficacy scale international. Another study was also conducted to examine the effectiveness of developed reaction test APP (application) on assessing cognitive function and fall risk in elderly people. The second stage aimed to conduct large-scale experimental studies to examine the effectiveness of the test protocols on classifying fallers and non-fallers and identifying the underlying causes of high risk of falling. The final stage aimed to develop an inertial sensor-based fall-risk assessment prototype system to assess fall risk for future use with elderly people.

In terms of classifying fallers and non-fallers, we found that the fallers had worse performances than non-fallers on physiological, psychological and integrated functions of the human balance system. Among all fall-risk measures, ten most important measures were the information processing speed in the reaction test, short falls efficacy scale international score in fear of falling test, power density spectral (PSD) of acceleration medio-lateral (ML) for the vision system, angular velocity anterior-posterior (AP) for the vision system, PSD of angular velocity AP for postural stability, sit-stand jerk in the sit-to-stand five times test, PSD of angular velocity AP for the vision system, sit-stand duration in sit-to-stand five times test, angular velocity AP in timed up and go test, and maximal turning angular velocity in timed up and go test. Furthermore, six typical models were developed to classify fallers and non-fallers based on significant measures, including logistic regression (LR), linear discriminant analysis (LDA), classification and regression tree (CART), boosted tree (BT), random forest (RF), and support vector machine radial basic function (SVMRBF) models. The results indicated that the BT, RF, and SVMRBF models had excellent accuracy (>85%). The CART model had good accuracy (>75%), but the LDA and LR models had relatively low accuracies of about 70%. In order to identify the underlying causes of high fall risks,

the CART-PA method, which integrated the CART model and profile assessment method, was proposed to identify the factors of high risks of falling. The CART-PA method could generate reinforced results from these two methods, which not only identifies the main factors but also possible factors of high fall risks. Therefore, the CART-PA method could be a useful complementary tool for identifying underlying causes of high fall risks. Fall assessment prototype system included two parts, i.e., hardware and software. The hardware contained five wireless inertial sensors and one wireless data transmission device. The software was developed to filter and process the data, derive the measures, and assess the risk of falling. Compared with available systems in the market, our inertial sensor based prototype system was very promising in terms of powerful functions, portability and low-cost on assessing fall risk of the older people.

The findings from this study and the developed prototype system could be incorporated into clinical practice to reliably identify "at-risk" individuals and to diagnose the underlying risk factors of falls in advance so that appropriate interventions can be implemented to reduce elderly people's risk of falling. Such a system could improve their quality of life and reduce costs in the healthcare system.

Acknowledgements

I would never have been able to complete my dissertation without the guidance of my committee members, the help and support from the kind people around me, to only some of whom it is possible to give particular mention here.

Firstly, I would like to express my sincere gratitude to my supervisor and mentor Professor Shuping Xiong for his time, ideas and the continuous support for my PhD study, and providing me with an excellent atmosphere for conducting the research. I have been very lucky to have a supervisor who took care of me like the elder brother in my life and encourage me to pursue high-quality research studies. His excellent guidance, caring, patience, and encouragement helped me to overcome many difficulties and improved my research ability.

I also want to express my sincere thanks to my thesis examination committee members: Professor Ravindra S. Goonetilleke for providing me valuable suggestions on my research study, especially on center-of-pressure based body sway assessment, Professor Gwanseob Shin for great support, encouragement and sharing facilities with us for my PhD study, Professor Sang Hoon Kang and Professor Oh-Sang Kwon for helpful suggestions and valuable time on my thesis.

I would like to acknowledge my good friends and lab mates: Yohana Siswandari, Taekyoung Kim and Woojoo Kim. Thanks goes to Yohana for giving me useful suggestions on dissertation writing and correcting grammar mistakes in my dissertation. Thanks goes to Taekyoung for helping me to arrange and conduct the major experiments in the elderly centers. A special thanks goes to Woojoo for helping me deal with language issues in my experiments and daily life. Many thanks to Mosis, Nam, Hwayeong Kang, Donghoon Kang, Liangjie Guo for fun time at UNIST.

I would like to give very special thanks to my parents for supporting me and granting me to pursue a PhD degree in South Korea. I also want to thank Ms. Yulei Shi for always trusting me, cheering me up and standing by me through the whole study period. Thanks to them, I could fully put my efforts on my study.

This study was funded by the Basic Science Research Program through the National Research Foundation of Korea (NRF 2011-0022185, NRF-2014R1A1A2056193).

Contents

List of Figures

List of Tables

Abbreviations

AP	**A**ntero**P**osterior
APP	**APP**lication
AUC	**A**rea **U**nder the ROC **C**urve
BT	**B**oosted **T**ree
CART	**C**lassification **A**nd **R**egression **T**ree
CES	**C**omposite **E**quilibrium **S**core
CNS	**C**entral **N**ervous **S**ystem
ES	**E**quilibrium **S**core
FES-I	**F**alls **E**fficacy **S**cale **I**nternational
GUI	**G**raphical **U**ser **I**nterface
LR	**L**ogistic **R**egression
LDA	**L**inear **D**iscriminant **A**nalysis
LOS	**L**imits **O**f **S**tability
ML	**M**edio**L**ateral
MF	**M**otor **F**unction
PSD	**P**ower **S**pectral **D**ensity
RF	**R**andom **F**orest
RMS	**R**oot **M**ean **S**quare
ROC	**R**eceiver **O**perating **C**haracteristic
ROM	**R**ange **O**f **M**otion
SIT	**S**ensory **I**ntegration **T**est
SOM	**S**omatosensory system
STS5	**S**it **T**o **S**tand **5** times

TUG	**T**imed **U**p and **G**o test
VES	**V**estibular system
VIS	**V**isual system
SFES-I	**S**hort **F**alls **E**fficacy **S**cale **I**nternational
SVM	**S**upport **V**ector **M**achine
SVMRBF	**S**upport **V**ector **M**achine **R**adial **B**asic **F**unction

Chapter 1

Introduction

1.1 Research Background

Falls present a substantial public health problem in older population (Kim and Robinson, 2005). Approximately one third of those aged 65 or over experience at least one fall per year (Rubenstein, 2006). As the age increases from 65 to 85 years old, fall rate increases from 30% to 50% and fall frequency increases from 1 to 3 or more (Lord et al., 1993). Falls are a leading cause of non-fatal injury and death in older people (Yu et al., 2013). They accounted for 95% of hip fractures (Parkkari et al., 1999), 40% of injury-related deaths (Lord et al., 2007) and 70% of accidental deaths in persons aged 75 years and over (Fuller, 2000). Falls not only result in serious consequences on physiological functions such as mobility, but also induce the fear of falling (Bell et al., 2000). The fear of falling causes old people to limit their activities, which will consequently enhance the loss of mobility and physical fitness, and in turn increase their risks of falling (Vellas et al., 1997). Furthermore, the average treatment cost of a fall ranges from \$3476 per fall to \$10749 for an injurious fall and \$26483 for a fall requiring hospitalization. The annual cost of non-fatal and fatal falls was around \$23.3 billion (2008 prices) in the US (Davis et al., 2010). Fall-related injuries have been considered as an outgrowing economic burden (Sartini et al., 2010) and parts of 'Global Burden of Disease' by World Health Organization (Mathers et al., 2008).

Fall prevention and management, which aims to reduce the risks of falls and to avoid or mitigate fall-related injuries, includes three areas. These areas are fall prevention (before a fall event), fall detection and monitoring (fall tracking), and post-fall management (after a fall event) (Taylor et al., 2005). Before a fall occurs, fall prevention intends to predict fall risk, identify the risk factors of falls, and design an intervention strategy. Fall detection concerns issuing an alert once a fall occurs, to request immediate help from family members or health care service center (Gurley et al., 1996). Post-fall management involves careful evaluation and investigation to identify risk factors and to prevent future incidents after a fall occurs (VA National Center for Patient Safety, 2015). The negative consequences resulting from falls are always irreversible. Fall prevention provides the methods to avoid the related injuries before a fall occurs. Therefore, compared with fall detection and post-fall management, fall prevention is a more effective way to reduce fall-related injuries and injury-related health care cost. In this regard, a great number of studies have been done to assess fall risks and design interventions to prevent falls before a real fall happens (Hamacher et al., 2011; Howcroft et al., 2013; Piirtola and Era, 2006; Rubenstein, 2006).

Fall prevention comprises fall risk assessment and fall intervention (Rubenstein, 2006). Fall risk assessment aims to predict the fall risks of a person and then identify important risk factors of falls if the person is at a high risk. Once the risk factors are determined, fall intervention will be utilized to improve the physiological performance of the person through therapeutic approaches or rehabilitation programs. A great number of measures were found to be useful on distinguishing fallers and non-fallers (Hamacher et al., 2011; Howcroft et al., 2013; Piirtola and Era, 2006). For example, the temporal measures of swing and stance in gait patterns were the most effective in distinguishing fallers and non-fallers (Hamacher et al., 2011). Amplitudes of acceleration and angular velocity from inertial sensors also showed significant differences between fallers and non-fallers (Greene et al., 2012). In addition, Michael et al. (2007) indicated that many falls could be prevented through customized multi-component interventions. They also found that exercise programs, rehabilitation, medication management, and treatment of vitamin D deficiency were some of the most effective single interventions.

Therefore, this research would mainly focus on fall risk assessment. The outcomes from this research are expected to be useful for identifying the high risk individuals and identifying the underlying causes so that proper interventions can be developed to efficiently prevent falls.

1.2 Literature Review

1.2.1 Fall risk factors

A fall is usually defined as ”an event which results in the person coming to rest inadvertently on the ground or other lower level, and other than as a consequence of the following: sustaining a violent blow, loss of consciousness, sudden onset of paralysis, or an epileptic seizure.” (Kennedy, 1987). The occurrence of a fall is a multi-factor phenomenon among the elderly (Kenny et al., 2011). A large number of risk factors of falling (Masud and Morris, 2001) have been identified among the old people. These factors are broadly classified into two major categories (Lajoie and Gallagher, 2004): intrinsic and extrinsic factors.

Intrinsic factors include characteristics of the individual. Some are demographic factors, such as age and gender. As the age increases, human’s physiological abilities declines, which results in high fall risks of old adults. The Center for Disease Control and Prevention (CDC) reported that fall injuries rate among people aged 75 or over was four or five times higher than people aged between 65 and 70 in Unite State (Centers for Disease Control and Prevention, 2015). Women were reported to be 58% more likely than men to suffer a nonfatal fall injury (Dunlop et al., 2002). Other factors are related to physiological function, such as vision, vestibule, cognitive function, muscle strength and gait pattern. Impaired depth perception was found to be one of the strongest visual risk factors for multiple falls (Salonen and Kivelä, 2012). Vestibular dysfunction could result in impairments in posture and gait, characterized by postural instability and a broad-based, staggering gait pattern with unsteady turns (Sturnieks et al., 2008). Moreland et al. (2004) found that for lower extremity weakness, the combined OR is 1.76 (95% CI=1.31-2.37) for any fall and 3.06 (95% CI=1.86-5.04) for recurrent falls. In a meta-analysis of 27 studies, Muir et al. (2012) found that many measures of cognitive impairment were associated with increased fall risk (OR=2.13 CI=1.56-2.90). Gait disorders have been considered as one of strongest risk factors of falls in multiple review studies (Deandrea et al., 2010; Hamacher et al., 2011). Additionally, psychological characteristics also were important intrinsic factors, such as depression and fear of falling. The depression are common in certain neurological conditions such as stroke, Parkinson’s disease, Alzheimer’s disease, and dementia (Boswell and Stoudemire, 1996; Wang et al., 2012). As a result, these patients would have limited mobility and poor balance ability, and thus predispose to falls. The fear of falling also has been identified as one of the key symptoms of ’past-fall syndrome’ (Legters, 2002). Individuals with fear of falling intended to avoid activities that could result in movement restriction and loss of independence. (Legters, 2002).

Extrinsic or environmental factors comprise all influences external to a subject, such as poor lighting, obstacles, slippery floor or loose rugs, lack of support such as stair railings or grab bars, poor fitting footwear (Ambrose et al., 2013; Hamacher et al., 2011). Poor lighting and obstacles inside the house, such as loose rugs may increase the risk of falls, especially for individuals with a visual impairment (Menz et al., 2006). Footwear is another import factor that affects postural stability and hence results in accidental falls (Menz et al., 2006). A large number of older adults tend to wear slippers while they are at home (Koepsell et al., 2004). In a systematic review, Menant et al. (2008) reported that older people who wore slippers had a higher fall risk score than those whom walked barefoot or with fastened shoes. Walking barefoot or with socks can also increase the risk of falling by up to 11 fold compared with walking with athletic or canvas shoes (Menant et al., 2008; Tencer et al., 2004).

Until now more than 400 risk factors of falls have been proposed in previous studies (Hamacher et al., 2011). Thus, the next important step is to identify the factors of high importance among all these factors. In a recent review of 12 studies, Inouye et al. (2007) identified older age, functional impairment, use of assistive device such as a walking aid, cognitive impairment or dementia, impaired mobility or low activity level, and balance abnormalities as the main causes of falls in older adults. Ganz et al. (2007) also reported that the most consistent predictors of future falls were clinically abnormal gait or balance disorders (likelihood ratio range: 1.7-2.4). Two more recent systematic reviews also found that gait and balance were major factors that were the most highly correlated with fall risk (Ambrose et al., 2013; Tinetti and Kumar, 2010). According to these studies, almost important factors were intrinsic factors. Therefore, intrinsic factors (particularly gait and balance) can not only be quantified, but also have consistently been considered as the major risk factors of falls.

1.2.2 Fall related factors based on human balance system

Human balance refers to the ability of a person not to fall (Pollock et al., 2000). As human being are bipeds with both feet on the ground during standing, one foot in contact when walking, and no feet in contact during running, it is a major challenge to keep balance. Since two-thirds of our body mass is located two-thirds of body height over the ground, we are in an inherently unstable status unless a control system is continuously acting to achieve balance. This control system is also called human balance system (Watson and Black, 2008; Winter, 1995).

The human balance system involves complex components of sensorimotor-control systems (Figure 1.1), which includes sensory inputs from the vision, somatosensory system, and vestibular system; integration of sensory inputs; and motor output to the appropriate body segment (Winter, 1995). In sensory systems, vision is a system which is primarily involved in planning our locomotion, and in avoiding obstacles along the way. The vestibular system is our 'gyro', which senses linear and angular accelerations. The somatosensory system is a multitude of sensors that sense the position and velocity of all body segments, their contact (impact) with external objects (including the ground, and the orientation of gravity). The information from the sensory systems is sent to the central nervous system (CNS) in the brain stem. There, it is sorted out and integrated with learned information contributed by the cerebellum (the coordination center of the brain) and the cerebral cortex (the thinking and memory center). As sensory integration takes place, the brain stem transmits impulses to the muscles that control movements of the eyes, head and neck, trunk, and legs, thus allowing a person to both maintain the balance and also have clear vision while moving.

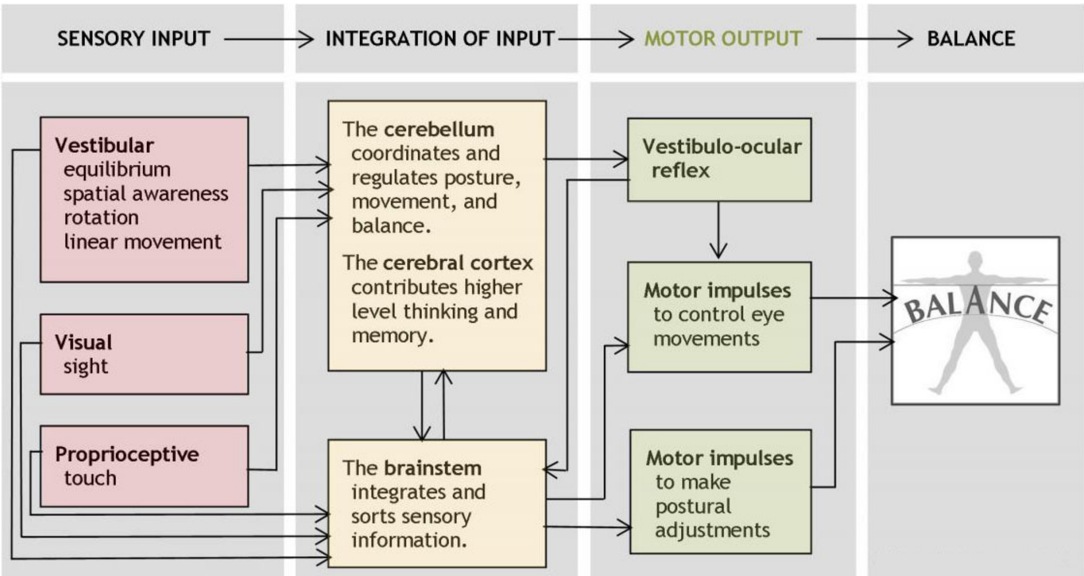


FIGURE 1.1: Components of human balance control system for achieving balance (Watson and Black, 2008) .

In addition, balance control is very complex process and involves many different underlying systems

(Horak, 2006; Horak et al., 1989; Kandel et al., 2000). Horak et al. (2009) proposed six underlying balance control systems based on the tasks in the Balance Evaluation Systems Test (BESTest). These underlying systems are biomechanical constraints, stability limits/Verticality, anticipatory postural adjustments, postural response, sensory orientation, and stability in gait. Each underlying system was found to be controlled by independent neural mechanisms (Horak et al., 1989, 2009). Many different tests have been designed to evaluate these underlying systems, for example center of mass alignment test in biomechanical constraints, functional reach test in stability limits, sit to stand five times test in anticipatory postural adjustment, in-place response test in postural responses, sensory integration test in sensory orientation, and timed up and go test in stability in gait (Horak et al., 2009).

Therefore, fall related factors are associated with three main system functions: the physiological function, psychological function and integrated function. The physiological function is about the function of individual components of the balance control system (Watson and Black, 2008). In addition to the physiological function, the psychological function was also found to affect fall risks, such as fear of falling. Fear of falling has been identified as one of the key symptoms of 'past–fall syndrome' and it has been recognized as a specific health problem among older persons (Legters, 2002). Integration function is related to the underlying systems in human balance control. It can be classified into six categories: biomechanical constraints, sensory orientation, stability limits, anticipatory postural adjustments, postural response, and stability in gait (Horak et al., 2009).

1.2.3 Fall risk assessment methods

Many different tools and technologies have been applied to assess fall risk. These methods can be classified into subjective and objective evaluations. Subjective evaluation is related to rate the subject's performance based on human judgment. Due to the low cost and convenience in practice, subjective evaluation tools are quite popular among the existing clinical methods. For example, the Berg Balance Scale (BBS) was a widely used clinical test to measure a person's static and dynamic balance ability (Berg et al., 1992). The test comprises a set of 14 simple balance related tasks, ranging from standing up to standing on one foot. BBS was found to be one of the effective fall predictors for falls within old adults (Shumway-Cook et al., 1997). Falls efficacy scale-international (FES-I), which evaluates how much concerns of falls affect activities of daily living, is a commonly used tool measuring fear of falling (Yardley et al., 2005). FES-I also showed a good ability on differentiating fallers and non-fallers (Helbostad et al., 2010).

However, subjective evaluation is always influenced by observer's personality and experience. On the other hand, objective evaluation qualifies a subject's performance by the equipment and is impartial without bias or prejudice. Based on the equipment, it includes some clinical tools such as timed up and go test using a stopwatch, posturography using force plate, optical motion capture system, and inertial sensors. Some objective clinical assessment tools are very popular due to the simplicity and convenience. For example, timed up and go test is a simple test that is used to assess a person's mobility (Podsiadlo and Richardson, 1991). In the test, a person is asked to rise from a chair, walk three meters, turn around, walk back to the chair, and sit down. Previous studies showed that the timed up and go (TUG) test was a useful tool for distinguishing fallers and non-fallers (Beauchet et al., 2011). But clinical assessment tools have limited measures. For example, duration is the main objective measure in the TUG. Many advance equipment based methods were also utilized to assess fall risks. Posturography is the quantitative assessment of postural sway during standing using a force plate. It contains static and dynamic conditions. Static posturography consists of assessing postural control while subjects maintain their stance in a relatively unperturbed state. Dynamic posturography consists of assessing the subject's postural control in the presence of experimentally induced external perturbations. This can be done by means of a foam cushion, a special apparatus with a movable support surface, or by applying external perturbations directly to the body, for example by pushing/pulling the trunk, shoulders or pelvis (Visser et al., 2008). For example, sensory perturbation is to separate the sensory inputs for postural control by using foam cushion or movable support surface. In the Balance Master Pro (Neurocom Inc.), a commercially available system, the Sensory Organization Test (SOT) is designed to measure the visual, vestibular, and somatosensory systems (Baker, 2003). Different from posturogarphy using the force plate, optical motion capture system is commonly used to assess the mobility and gait stability. Gait stability measures, such as walking velocity, step width, swing and stance time, were found to be significant measures on distinguishing fallers and non-fallers (Hamacher et al., 2011).

Recently, researchers have showed a great interest in using wireless wearable inertial sensors to assess fall risks (Howcroft et al., 2013). The inertial sensor is a combination of an accelerometer, a gyroscope and a magnetometer that can measure the accelerations and angular velocity of body movement.

Compared with the force plate and optical motion capture system, the wireless sensors have big advantages on low cost, small size, and portability. Additionally, inertial sensors can be used to measure postural stability during the standing, as well as gait stability during walking or running. Mancini et al. (2011) have demonstrated that postural sway measures derived from sensor data can generate similar sway characteristics as measures from the force plate. Inertial sensor based postural stability measures also showed significant differences between fallers and non-fallers during quite standing (Greene et al., 2012). Furthermore, gait stability measures could be extracted from the sensor raw data, such as stride velocity, stride width, cadence, swing time and stance time (Zijlstra and Hof, 2003). These measures also demonstrated the significant differences between fallers and non-fallers during timed up and go test (Greene et al., 2010a).

1.3 Research Rationale

The literature review showed that many studies have designed different tasks and utilized different technologies to assess fall risks. However, there are still some gaps in the current fall risk assessment methods that need to be filled.

Firstly, since falls are multifactorial phenomenons, more than 400 risk factors were found to be associated with falls from previous studies (Hamacher et al., 2011; Oliver et al., 2004). However, many factors used to assess fall risk were uncontrollable or unmodifiable. Some environmental factors are generally uncontrollable, such as lighting, surface roughness, obstacle or external perturbations (Hamacher et al., 2011). Other factors are inherent properties of human being, for example demographic factors such as age and gender (Ambrose et al., 2013). Additionally, many studies used only parts of factors to assess fall risks. For example, the study of physiological profile assessment (PPA) only focused on the individual components of physiological systems that were associated with falls (Lord et al., 2003b). Horak et al. (2011) argued that integration functional ability was not only dependent on individual components of physiological system function, but also had compensations between the systems, remaining resources, experience and other factors. PPA was limited to individual function evaluation, so Horak et al. (2009) proposed BESTest methods to assess integration function of systems in different tasks. However, both PPA and BESTest did not consider the psychological characteristics of a person such as fear of falling, which had been found as a common problem in fallers even non-fallers (Legters, 2002). Even though

PPA included many physiological factors and BESTest developed the approaches to assess integration system functions, few studies selected fall risk factors systematically, which could include individual physiological function, psychological function and integration function. Consequently, if the selected factors were not systematic, the underlying reasons of falls may be not identified due to the absence of some factors. Among risk factors, central nervous system (CNS) integrates the inputs from sensory systems (vision, vestibular and somatosensory systems) and responds as adjusting muscles and joints to achieve balance (Horak, 2006; Winter, 1995). It has been documented that cognitive processing was the required resource for postural balance control (Horak, 2006). Neuropsychological testing assesses a range of cognitive abilities such as memory, attention and concentration, information processing speed, executive function, reasoning, etc (Harvey, 2012; Kulas and Naugle, 2003). The literature showed that reaction time has been widely used to measure the information processing speed (Lajoie and Gallagher, 2004). Previous studies of older people found that increased simple reaction time (SRT) and choice reaction time (CRT) were significant risk factors for falls (Grabiner and Jahnigen, 1992; Lord and Clark, 1996; Woolley et al., 1997). SRT used a light as the stimulus and pressing of a switch by the hand as the response (Lord and Clark, 1996). In CRT task, the participant was required to kick a 10×10 target beneath one of the three stimulus lights that were illuminated (Woolley et al., 1997). They also reported that fallers were significantly slower than non-fallers in SRT and CRT tests. A new test of choice stepping reaction time (CSRT) was also proposed to assess fall risks and the results showed that fallers had significantly increased CSRTs compared with non-fallers (Lord and Fitzpatrick, 2001). However, some studies (Jensen and Munro, 1979; Mahurin and Pirozzolo, 1993) argued that reaction time may fail to measure the information processing efficiently since reaction time contains not only the time of perception and information processing but also motor planning time. All these tests involved motor functions to respond to the stimulus, such as SRT task using the hand to press a switch as the response to the stimulus of a light (Lord and Clark, 1996), simple and choice resisted knee extension response times using the lower leg to kick the target below the stimulus lights that illuminated (Woolley et al., 1997), and CSRT involving the balance of the whole body to step on the illuminated panel as the response to the stimulus light. As a result, longer reaction time may result from worse motor functions due to weak muscle strengths or other motor deficits. Therefore, reaction time in these tasks could be inadequate to assess information processing efficiency.

Secondly, many assessment approaches or models have been developed to classify fallers and non-fallers, but they lack of ability to further identify the underlying reasons. Tromp et al. (2001) constructed logistic regression model to predict falls using the predictors of previous falls, visual impairment, urinary incontinence, use of benzodiazepines,and functional limitations. In another study, Stalenhoef et al. (2002) also used logistic regression model to develop fall prediction model and found that postural sway, previous falls, hand grip strength, and depressive state of mind were strong predictors of recurrent falls. Although many published studies in this research area (Bongue et al., 2011; Chen et al., 2005; Lajoie and Gallagher, 2004; Mackintosh et al., 2006; Pluijm et al., 2006; Shumway-Cook et al., 1997; Stel et al., 2003b; Swanenburg et al., 2010) succeeded in figuring out the important measures for discriminating fallers and non-fallers, the models used in these studies were unable to identify the underlying causes of high fall risks. In an effort to identify the causes of high fall risks, two approaches have been proposed in previous studies. Lord et al. (Lord et al., 2003b) proposed profile assessment to identify the causes of high fall risks. The reference ranges of normal performance for test results can be generated from large scale data. A subject's test results were compared with the reference range to determine whether related functions were impaired or not. The other method was to use tree based models including tree-structured survival analysis (Stel et al., 2003a), classification and regression trees (Delbaere et al., 2010), and logistic regression tree analysis (Yamashita et al., 2012). However, the factors in their studies were not systematic and included many unmodifiable items, such as age (Yamashita et al., 2012) and education (Stel et al., 2003a).

Lastly, by using a force platform, posturography which includes static and dynamic conditions was popular in assessing static and dynamic balance during standing (Piirtola and Era, 2006). The optical motion capture system was also used to analyze the gait patterns for assessing fall risks (Hamacher et al., 2011). However, force plate and optical motion capture system are expensive, heavy and/or required large space. Additionally, when standing on a forceplate, center of pressure based body sway measures were reported to fail to distinguish fallers and non-fallers (Qiu and Xiong, 2015). On the other hand, recently inertial sensors are frequently used to assess fall risk in many studies (Howcroft et al., 2013) due to the low-cost and portability of the sensors. Hence, compared with force plate and optical motion capture system, the inertial sensor technology was more convenient to assess fall risks. Since most falls occur during dynamic activities such as walking (Granata and Lockhart, 2008), inertial sensors were also efficient on evaluating dynamic activities, such as gait patterns during timed up and go test (Greene et al., 2012). Furthermore, in previous studies, many inertial sensor based measures were found to be capable of separating fallers and non-fallers and were classified into six categories (Howcroft et al., 2013). They were position and angle variables such as peak to peak amplitude in anterio-posterior (AP) direction (Ishigaki et al., 2011), angular velocity variables such as maximal angular velocity in AP direction (Greene et al., 2010a), linear acceleration variables such as peak acceleration in AP direction (Weiss et al., 2011), spatial variable such as number of steps, temporal variables such as gait speed (Marschollek et al., 2009), and energy variables such as sway frequency when during (Greene et al., 2012). Furthermore, fall risk assessment models have also been developed to assess fall risks using those significant measures, such as support vector machine (SVM) (Greene et al., 2012), radial basis function neural network, support vector, k-nearest neighbor, and Naive Bayesian classifiers (Caby et al., 2011). However, as far as we know, no previous studies have developed inertial sensor based fall assessment system for identifying the underlying causes of high fall risks.

1.4 Research Objectives

This research aimed to develop a low-cost and portable tool that can not only predict fall risks but also identify underlying causes of high fall risks among the older people. There were three stages in this research.

The first stage of the research aimed to design a human balance system based test protocol for fall risk assessment and evaluate the effectiveness of a new test on assessing fall risks. First, measurable, modifiable and important fall related factors were summarized based on human balance system and an extensive literature review. The first study was to design a human balance system based test protocol that was corresponding to these fall related factors for assessing risks of falls. Many useful tests on fall assessment in previous studies were selected and directly included into the test protocol. But some limitations still existed in current studies of reaction tests on assessing the central nervous system of cognitive function. So we developed our own reaction test AP based on Hick's law in test protocol. Thereby another study was to examine the effectiveness of developed reaction test APP on assessing cognitive function and fall risk in old people.

- **Study I:** Design of a new test protocol (Chapter 2).
- **Study II:** Validation of a reaction test APP on assessing fall risks (Chapter 3).

The second stage aimed to conduct large-scaled experimental studies to check the effectiveness of the test protocols on classifying fallers and non-fallers, and identifying the underlying causes of high fall risks. After the experiment, significant measures that were associated with fall risk factors in the tests were used as independent variables and fall history was used as dependent variables to construct fall classification models. Six typical models including logistic regression (LR), linear discriminate analysis (LDA), classification and regression tree (CART), boosted tree (BT), random forest (RF), and support vector machine radial basic function (SVMRBF) were built to classify fallers and non-fallers. Furthermore, CART model and the profile assessment were integrated and utilized to identify the underlying causes of high fall risks.

- **Study III:** Fall classification (Chapter 4).
- **Study IV:** Fall evaluation (Chapter 5).

The final stage aimed to develop an inertial sensor based system for realizing the fall risk assessment methods in the second stage for future application.

- **Study V:** An inertial sensor based fall risk assessment system development.

1.5 Thesis Organization

The overall structure of this dissertation is presented in Figure 1.2. Below is the summary of the seven chapters contained in this dissertation.

Chapter 1 introduces research background, literature review, research rationale, and research objectives. This chapter also provides the structure of this dissertation.

Chapter 2 involves the design of a new test protocol based on human balance system by mainly using inertial sensors for fall risk assessment. The design considerations and general principle were explained and the details of tests in the test protocol were described.

Chapter 3 investigates the effectiveness of the reaction test APP based on Hick's law on assessing cognitive function and fall risk in old people. This chapter presents the design and work mechanism of reaction test APP, the experimental design and the detail procedures of the experiment. The experimental results are also presented and discussed.

Chapter 4 is to develop the models for classifying fallers and non-fallers. In this chapter, the experimental procedures, data processing to generate measures from the tests and the construction of fall classification models are presented and followed by the results. Then the results are discussed.

Chapter 5 is about the methods to identify the underlying causes of high fall risks. This chapter presents the methods of fall evaluation and followed by the results. Then the results are discussed.

Chapter 6 presents the development of inertial sensor based fall risk assessment system. This chapter first explains the principle of designing the system and then presents the hardware and software of system. The performance of the system is discussed.

Chapter 7 concludes the dissertation by summarizing the main findings and re-addressing the research objectives, followed by a discussion on the limitations and future works of the current study.

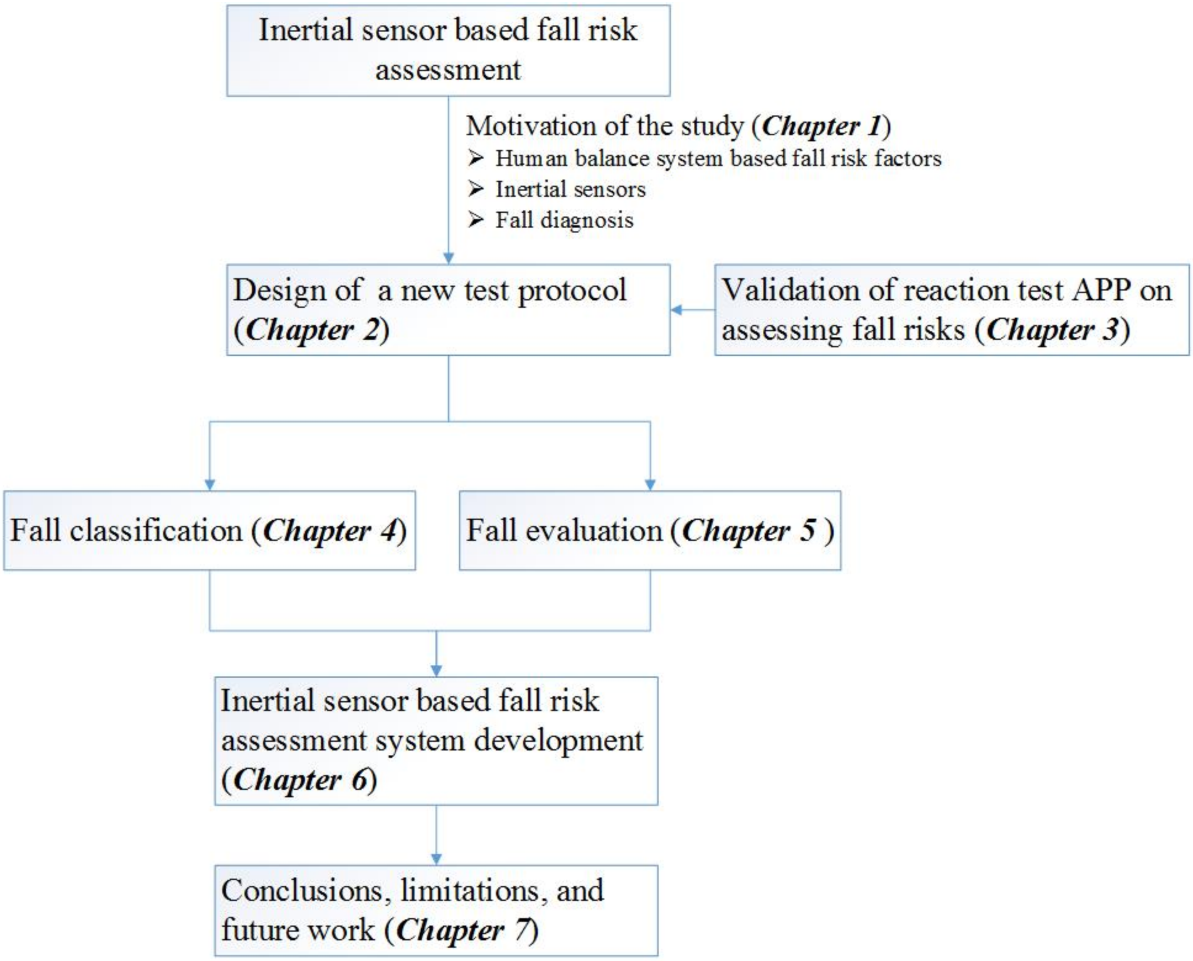


FIGURE 1.2: The dissertation outline.

Chapter 2

Design of a human balance system based test protocol for fall risk assessment

2.1 Introduction

Many tests have been developed to assess fall risks factors related to the human balance system. Contarino et al. (2003) used a test to evaluate the performance of the sensory system. The test consists of four conditions: (1) stand on a firm surface with the eyes open; (2) stand on a firm surface with the eyes closed; (3) stand on a compliant surface (foam) with the eyes open; and (4) stand on a compliant surface (foam) with the eyes closed. A modified clinical test of sensory interaction and balance also includes these four conditions (Whitney and Wrisley, 2004). In the test, a stop watch is used to measure the maximal time (a maximum of 30 seconds) for maintaining the standing position. Similarly, a commercial system, Balance Master Pro (NueroCom Inc.), also contains this test, which is called the modified sensory integration test to evaluate the performance of the sensory system based on interaction with a force plate. In the system, the center of gravity (COG) is generated by the system to measure the performance. Recently, using the sensory related test, inertial sensor based measures have been proposed to assess postural sway (Mancini et al., 2012). O'Sullivan et al. (2009) found a significant difference in acceleration RMS for condition 3 between fallers and non-fallers. Greene et al. (2012) also indicated that fallers had significantly higher accelerations and angular velocity than non-fallers during conditions 1 and 2.

Reaction time was defined as the duration measured between the presentation of an unexpected stimulus and the onset of a response to that stimulus (Schmidt and Debû, 1993). It has been widely used to measure the information processing speed of the central nervous system (Lajoie and Gallagher, 2004). Simple Reaction Time (SRT) is a test that measures the simple reaction time through delivery of a known stimulus to a known location to elicit a known response. Choice Reaction Time (CRT) is a 2-choice reaction time test which is similar to the (SRT) test, except the stimulus and response uncertainty are introduced by having two possible stimuli and two possible responses. Increased simple reaction time (SRT) and choice reaction time (CRT) were significant risk factors for falls in older people (Grabiner and Jahnigen, 1992; Lord and Clark, 1996). A new test of choice stepping reaction time (CSRT) was also proposed to assess balance ability and fall risks(Lord and Fitzpatrick, 2001).

In motor function, poor muscular strength is one important factor resulting in falls (Horlings et al., 2008). In a review of 30 studies, Moreland et al. (2004) concluded that grip strength was the most common measure used for the assessment for the upper extremity strength. Lower extremity weakness was a statistically significant risk factor for falls. Hand held dynamometry was considered as a convenient and reliable tool on measuring the muscular strength (Kelln et al., 2008; Spink et al., 2010). In addition, range of motion that reflects the flexibility of joints was also associated with fall (Tinetti et al., 1993) and fallers showed a significantly lower range of motion than non-fallers (Kerrigan et al., 2001; Tinetti et al., 1986).

In relation to psychological aspects, a questionnaire of falls efficacy scale international (FES-I) is commonly used to assess fear of falling (Tinetti et al., 1990). It consists of sixteen items that are related to daily activities such as going up or down stairs. Participants answer about how much they are concerned about falling in these various activities. The options range from 1 to 4: 1=not at all concerned, 2=somewhat concerned, 3=fairly concerned, and 4=very concerned. Recently, a short version of FES-I was also proposed to assess fear of falling (Kempen et al., 2008). Short FES-I only contained 7 of 16 items in FES-I and was found to be a good, feasible and valid measure to assess fear of falling in older adults (Kempen et al., 2008; Ruggiero et al., 2009). FES-I used a short and verbal phrase to state the overall context or activity, but does not specify more detailed contextual elements. Due to this, Delbaere et al. (2011) developed the Iconographical Falls Efficacy Scale (Icon-FES), which includes a broad range of activities and uses pictures to provide clear, unambiguous contexts. Icon-FES has been found to be a feasible, reliable, and valid tool for accessing fear of falling (Delbaere et al., 2013, 2011). Similarly, a questionnaire that is the activities-specific and balance confidence (ABC) scale was developed to measure the psychological impact of balance impairment and/or falls (Powell and Myers, 1995). It is a 16-item self-report measure in which patients rate their balance confidence for performing activities. Each item is stated as: "How confident are you that you will not maintain your balance or become unsteady when you...". Items are rated on a rating scale that ranges from 0-100, where a score of zero represents no confidence and a score of 100 represents complete confidence. Compared with FES-I, ABC has a wider continuum of item difficulty and is more suitable for moderate to high functioning older adults (Myers et al., 1998). Fallers also showed significantly higher falls efficacy scale scores than non-fallers (Delbaere et al., 2010; Friedman et al., 2002).

In addition to individual functions in a human balance system, the integrated function is about different control mechanisms when performing different tasks. As shown in Figure 2.1, the integrated function contains six aspects: biomechanics constrains, stability limits, anticipatory postural adjustments, postural responses, sensory orientation, and stability in gait (Horak et al., 2009). Many tests have been used to measure these functions. A sensory related test (Contarino et al., 2003) was associated with biomechanics constrains and sensory orientation. Duncan et al. (1990) developed a function reach test to measure stability limits, in which participants were required to reach forward as far as possible with their arm. The test was used to assess dynamic balance (Duncan et al., 1990; Franzen et al., 1999) and fall risk (Behrman et al., 2002; Franzen et al., 1999). Multi-direction reach tests that include forward, backward, left and right reach tests were also developed to assess fall risks (Newton, 2001). The sit-to-stand five times (STS5) test requires participants to do a sit-to-stand task five times as fast as possible, which measures anticipatory postural adjustments and postural responses. Total duration was found to be significantly associated with fall risk (2008). Doheny et al. (2011) found that fallers had a significantly longer sit-to- stand time, smaller jerk and higher spectral edge frequency than non-fallers in the STS5 test. Buatois et al. (2008) also indicated that the time needed to complete STS5 was a significant predictive value for recurrent falls in a population of community-living older participants aged 65 and older. A timed up and go test that measures mobility and gait stability was used to assess fall risks (Greene et al., 2010a,b). In the timed up and go test, fallers showed a significantly longer walk time and smaller angular velocity than non-fallers (Greene et al., 2010a). Gait pattern measures could be also generated based on inertial sensors (Greene et al., 2010b; Zijlstra and Hof, 2003). Fallers had significantly more gait cycles and steps, and longer step time than non-fallers (Greene et al., 2010a). Clinical tests also used a series of tests to assess fall risks. The Berg Balance Scale (BBS) was developed to measure standing balance by assessing the performance of functional tasks (1989). Previous studies showed BBS was a useful tool for assessing fall risks (Muir et al., 2008; Thorbahn and Newton, 1996).

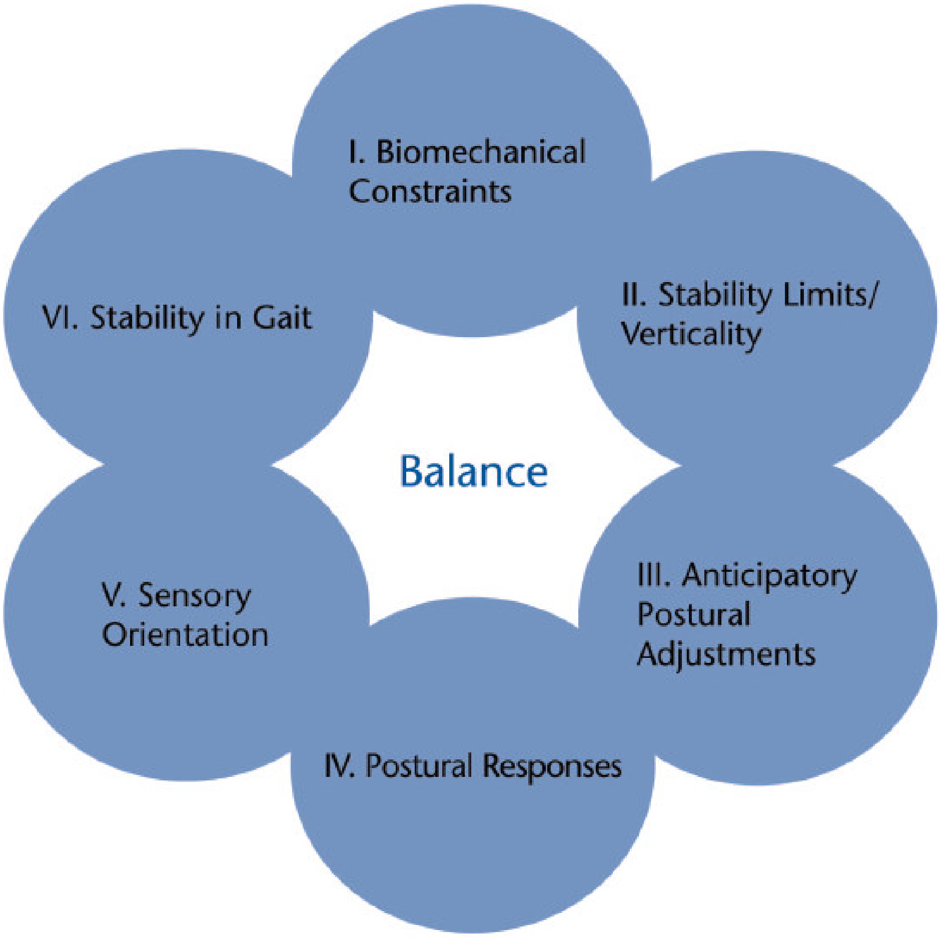


FIGURE 2.1: Components of integrated function in a human balance system (Horak et al., 2009).

Although numerous tests or measures showed significant differences between fallers and non-fallers, most of these tests or protocols were unable to identify the underlying reasons for high fall risks. Therefore, the objective of this section was to develop a human balance system based test protocol that could be effective on assessing risks of falling and identifying the underlying causes of high risks of falling.

2.2 Design consideration and general principle

In order for our developed risk assessment system to be practical and convenient for the older people, individual tests should meet the following criteria: (1) simple and quick to administer; (2) feasible for older people to undertake; (3) valid and reliable tests for assessing corresponding risk factors; (4) quantitative measures, which should be mainly obtained from wearable inertial sensors of accelerometers and gyroscopes. Based on the above criteria and the list of fall risk factors, seven tests (Figure 2.2) were proposed to assess those identified risk factors using related measures. Seven tests were generally widely reported and they were briefly as follows.

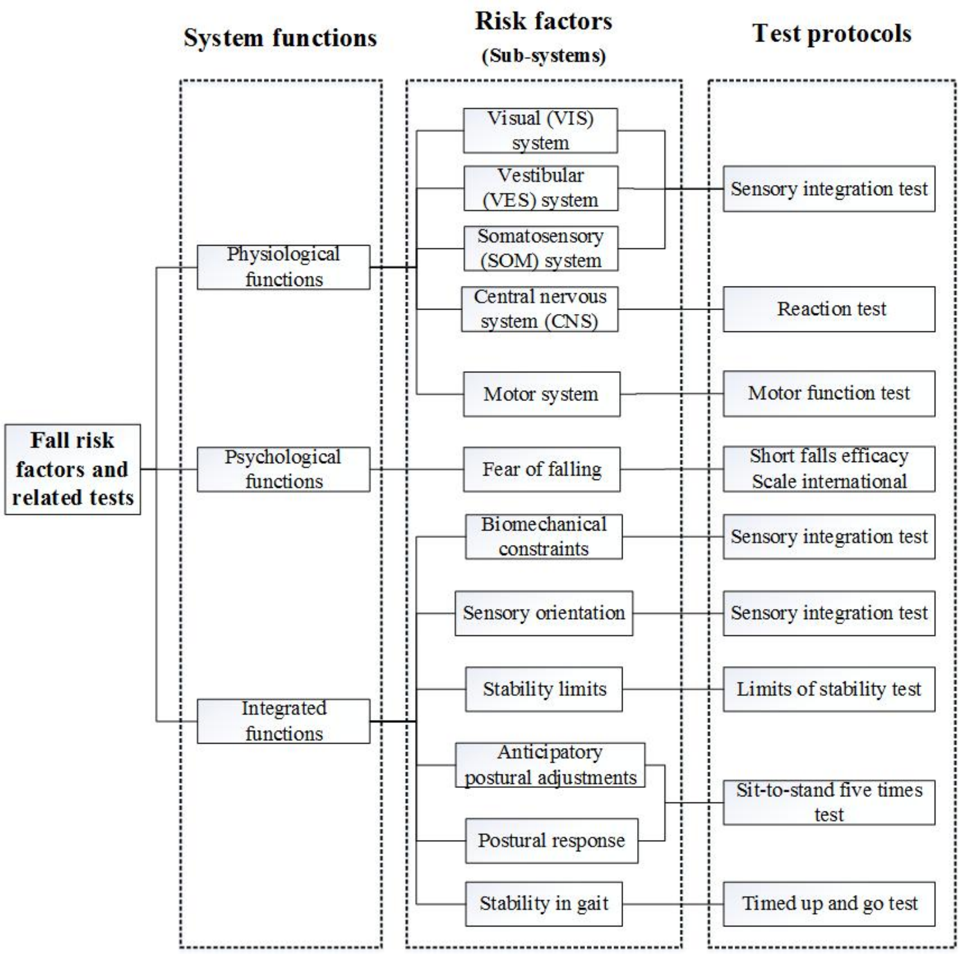


FIGURE 2.2: Relationships between the new test protocol and fall risk related factors

According to the human balance system, fall related factors included physiological, psychological and integrated functions (Figure 2.2). Physiological functions were associated with functions of individual systems within a human balance system. These systems included the sensory system consisting of the visual, vestibular and somatosensory systems, the central nervous system, and the motor control system. Psychological function was related to fear of falling. Integrated functions were associated with integration of physiological and psychological functions while performing different tasks.

In order to evaluate a sensory system, a sensory integration test (Details were described in Section 2.3.1) was used in this study. It was simple, easy, effective test, and was commonly used in previous studies (Whitney and Wrisley, 2004). The test satisfied our test criteria and was also able to evaluate the performance of sensory systems. Generally, a sensory system contained three main sub-systems, which are visual (VIS), vestibular (VES), and somatosensory (SOM) systems. During postural control, VIS are more influential than VES and SOM (Lee and Lishman, 1975; Soechting and Berthoz, 1979). When VIS is blocked, SOM is more important than VES at a stable condition (firm surface) but VES becomes more critical for postural control than SOM at an unstable condition (sway-reference or foam surface) (Horak and Hlavacka, 2001; Mergner and Rosemeier, 1998). Therefore, sensory system can be evaluated from the test measures in four conditions of a sensory integration test. These conditions are: (1) eyes open and stable surface; (2) eyes closed and stable surface; (3) eyes open and unstable surface; and (4) eyes closed and unstable surface. In order to measure each sensory system, Eliana et al. (2009) summarized the contributions of subsystems as follows:

$$SOM = \frac{condition2}{condition1} \times 100$$

$$VIS = \frac{condition3}{condition1} \times 100$$

$$VES = \frac{condition4}{condition1} \times 100$$

Therefore, sensory integration test was used to assess the sensory system.

The central nervous system (CNS) dealt with the stimuli from the sensory system and sent signals to the motor system to control muscles and joints for achieving the balance. Prior studies have widely used reaction time measures to assess human cognitive abilities such as information processing and executive functions (Lord and Fitzpatrick, 2001; Pijnappels et al., 2010). Increased simple reaction time (SRT), choice reaction time (CRT), and choice stepping reaction time (CSRT) were reported as significant risk factors for falls in older people (Lord and Clark, 1996; Lord and Fitzpatrick, 2001). However, some researchers (Jensen and Munro, 1979; Mahurin and Pirozzolo, 1993) argued that reaction time may fail to efficiently measure the information processing since it contains not only the time of perception and information processing but also motor planning time. Most tests involved motor functions to respond to the stimulus, such as SRT task using the hand to press a switch as the response to a light stimulus (Lord and Clark, 1996), and CSRT task involving the balance of the whole body to step on the illuminated panel as the response. As a result, longer reaction time may result from worse motor functions due to weak muscular strengths or other motor deficits. Therefore, reaction time alone in these tasks could be inadequate to assess human performance of the information processing. Taking into account limitations of the direct use of reaction time, Mahurin and Pirozzolo (Mahurin and Pirozzolo, 1993) applied Hick's law to examine the age-related neurological cognitive dysfunction in people with Alzheimer and Parkinson diseases. Hick's law describes the relationship between reaction time and task complexity (Hick, 1952; Hyman, 1953), and it states that human reaction time increases with a linear function to the logarithm of the number of alternatives. In the study of Mahurin and Pirozzolo (Mahurin and Pirozzolo, 1993), they used a timed card-sorting task and derived information processing speeds from the linear function based on Hick's law. They reported that Parkinson and Alzheimer patients showed significantly slower information processing speeds compared with healthy controls. However, to the best of our knowledge, no study has been conducted on applying Hick's law to measure information processing speeds for assessing the risk of falls in older people. Therefore, we developed a reaction test APP based on Hick's law for assessing cognitive function and falls risk in older people.

The motor system was related to the control of muscular strength and joints. As such, maximal muscular strengths and flexibility of lower extremities were measured directly in a motor function test. Fear of falling was examined by a questionnaire of short falls efficacy scale that measures how much a person is concerned about falling while performing some daily life tasks.

In the integrated functions, biomechanical constrains were related to postural stability and sensory orientation was about the overall performance of the sensory system. Both functions could be evaluated by the sensory integration test. Stability limits were assessed by limits of stability test, which evaluated the performance during the functional reaches in different directions. Anticipatory postural adjustments and postural response were about dynamic postural control ability while performing some tasks. These abilities were assessed in sit-to-stand five times test. Stability in gait was assessed by the timed up and go test, which required the participant to walk for 6 meters.

Most tests were common, simple, and easy to administer. Recently, sensing technology has become quite popular in the research area (Howcroft et al., 2013). Compared with traditional equipment such as force plate (Piirtola and Era, 2006) and optical motion capture system (Hamacher et al., 2011) for assessing fall risks, inertial sensors were much cheaper and more portable. Compared with qualitative assessment some clinical tests such as a clinical test of balance interaction test (Whitney and Wrisley, 2004) and Berg balance scale (Muir et al., 2008), inertial sensors provided more reliable and high quality data for various data analysis. Additionally, most tests could be measured by inertial sensors. In our experiment, five Xsens sensors, made by Xsens Inc, were utilized for data collection while participants performed these tests in the protocol. Sensors were attached on the body segments of the pelvis, left and right upper legs, and left and right lower legs (Figure 2.3).

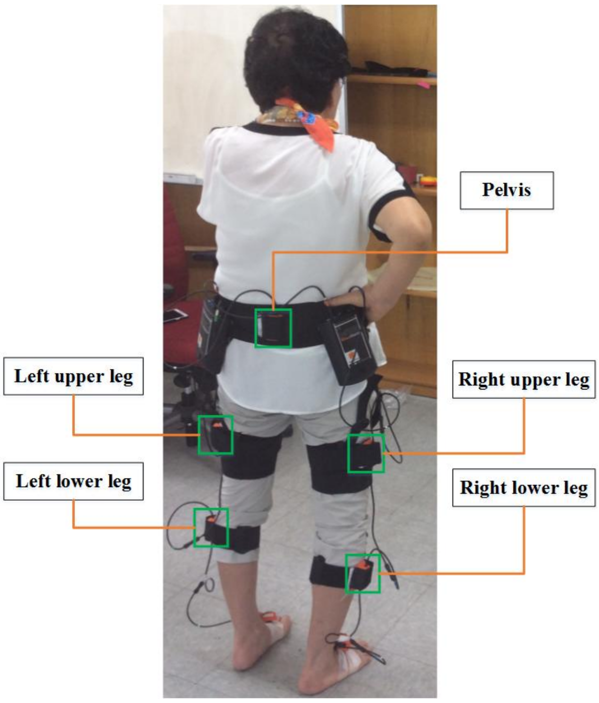


FIGURE 2.3: Sensor locations in the experiment. Xsens system requires at least seven sensors for data collections. In our experiment, only raw data from five sensors were utilized for further data analysis: pelvis, left and right upper legs, and left and right lower legs, but 2 sensors on foot were disabled.

In total, there were seven principal tests consisting of a sensory integration test, limits of stability test, sit-to-stand five times test, timed up and go test, motor function test, reaction test, and short falls efficacy scale. The new test protocol systematically covers fall related factors (Figure 2.2). Each function in the balance system was evaluated through the test. The overall performance in tests could be used to assess fall risks and also be applied to identify the causes of high risks of falling. (Demura and Yamada, 2007; Duncan et al., 2011; Greenberg, 2011; Herman et al., 2011; Khattar and Hathiram, 2012).

2.3 Details of the new test protocol

2.3.1 Sensory integration test

A sensory integration test (SIT) was designed to measure the sensory system, biomechanics constrains and sensory orientation. In the test (Figure 2.4), participants were asked to stand with bare feet as still as possible for 30 seconds, with arms at the side and looking straight ahead at a visual reference with eyes open in the following four conditions (O'Sullivan et al., 2009):

Condition 1: Eyes open with firm surface;

Condition 2: Eyes closed with firm surface;

Condition 3: Eyes open with a compliant foam mat (Airex Balance Pad Elite: $20 \times 16.4 \times 2.5$ inch);

Condition 4: Eyes closed with a compliant foam mat (Airex Balance Pad Elite: $20 \times 16.4 \times 2.5$ inch).

Each task was performed twice, during which the feet were positioned 10 cm apart. The visual reference was a black spot of 10 cm diameter and was 150 cm away from the participant.

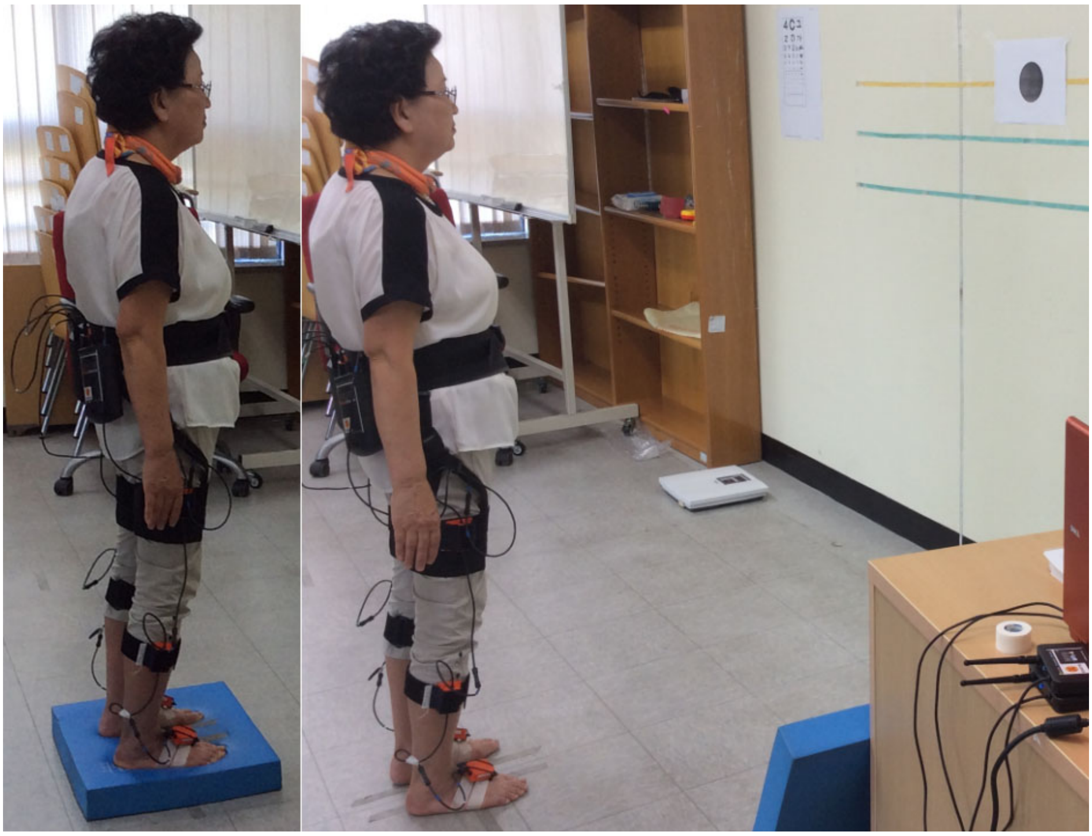


FIGURE 2.4: Experimental setting of sensory integration test.

2.3.2 Limits of stability test

The limits of stability (LOS) test was designed to measure stability limits during standing. It includes functional reach tasks in three directions: forward, left and right (Figure 2.5). In functional reach forward, a participant stood comfortably (feet width the same as shoulder width) with the right arm close and parallel to a wall but not touching. The right arm was positioned at 90 degrees of flexion with elbows and hands extended. The operator recorded the starting position at the third metacarpal head on the yardstick. Then the participant was instructed to reach as far as possible without taking a step. At this point, the operator located the third metacarpal as the end position. Subsequently, the participant returned to the start position. During the test, the left hand should be kept as close as possible to the body and both feet should fully touch the ground. Each participant was given at least one practice trial prior to the test, and three test trials were recorded later (Duncan et al., 1990). Functional reach left and right were similar as functional reach forward.

(a) (b) (c)

FIGURE 2.5: Experimental setting of limits of stability test. (a) forward reach; (b) left reach; (c) right reach.

2.3.3 Sit-to-stand five times test

The sit-to-stand five times test was designed to measure the ability of postural adjustment and response. In the test (Figure 2.6), a participant sat with arms folded across the chest and with their back against the chair in a standard chair (approximate seat height 18 inch, arm height 25.6 inch). She was then asked to stand up and sat down as quickly as possible on a firm, padded, armless chair. During the test, the participant was also instructed to keep the feet in a comfortable position and to sit with normal posture (the knee joint angle flexed around 90 degree) when sitting down on the chair and stood upright when standing (Schlicht et al., 2001). The test was performed twice.

(a) (b)

FIGURE 2.6: Experimental setting of sit-to-stand five times test. (a) sitting posture; (b) standing posture.

2.3.4 Timed up and go test

A timed up and go (TUG) was used to evaluate gait stability (Podsiadlo and Richardson, 1991). A participant sat in a chair with their trunk against the chair back and their arms resting on the chair arm. On the command "go", the participant rose from the chair, walked 3 meters at a comfortable and safe pace, turned around, and walked back to the chair and sat down (Figure 2.7). Each participant performed one practice trial and then three test trials.

FIGURE 2.7: Experimental setting of timed up and go test.

2.3.5 Motor function test

The motor function test mainly measured range of motion (ROM) of the knee joint and force production of the lower-extremity muscles that were maximal muscular strength of ankle dorsiflexion, knee extension and knee flexion. We measured ROM and muscle strength on the right leg of each participant. For the range of motion of knee extension (Figure 2.8a), the operator placed one hand above the knee joint and cupped the contralateral hand behind the heel to lift it off the bed until resistance was felt, which was deemed as the terminal extension. For range of motion of knee flexion (Figure 2.8b), the examiner put one hand on the thigh, and the other hand was placed on the anterior ankle with pressure applied to increase flexion until a firm endpoint was reached and maximum flexion determined (Peters et al., 2011).

In terms of measuring maximal ankle dorsiflexion strength (Figure 2.8c), the participant lied on a bed with feet over the edge of an examination table. The hand-held dynamometer was positioned against the metatarsal heads on the dorsal aspect of the foot (Carroll et al., 2013). Then the participant was asked to try her maximal efforts to perform ankle dorsiflexion to push the dynamometer as much as possible. Finally, maximal ankle dorsiflexion strength was measured on the dynamometer.

To measure maximal muscular strengths of knee extension and flexion (Figure 2.8d and e), the participant lied prone on the bed with the right lower leg flexing 90 degrees. The hand-held dynamometer was positioned against the extreme of the lower leg in flexion or extension. During the test, the participant was encouraged to flex or extend her knee to push the dynamometer as much as possible (Carroll et al., 2013). Maximal muscular strengths of knee extension and flexion were measured on the dynamometer.

In addition to muscular strength of the lower extremity, grip strength was the most effective measure of the upper extremity to assess fall risks (Moreland et al., 2004). So we also measured hand grip force. In the test (Figure 2.8f), according to the standardized positioning recommended by the American Society of Hand Therapists (ASHT) (Casanova, 1992), participants were seated with their shoulders in 0 degree abduction and neutral rotation, their elbows in 90 degree of flexion, and their forearms in neutral pronation supination. The test was also done on the right hand.

Each participant performed sub-maximal test movements for the familiarization prior to testing. Testing of each muscle group required a contraction of 3-seconds. Three repetitions were obtained for each muscle group, with a minimum rest period of 10 seconds between each contraction.

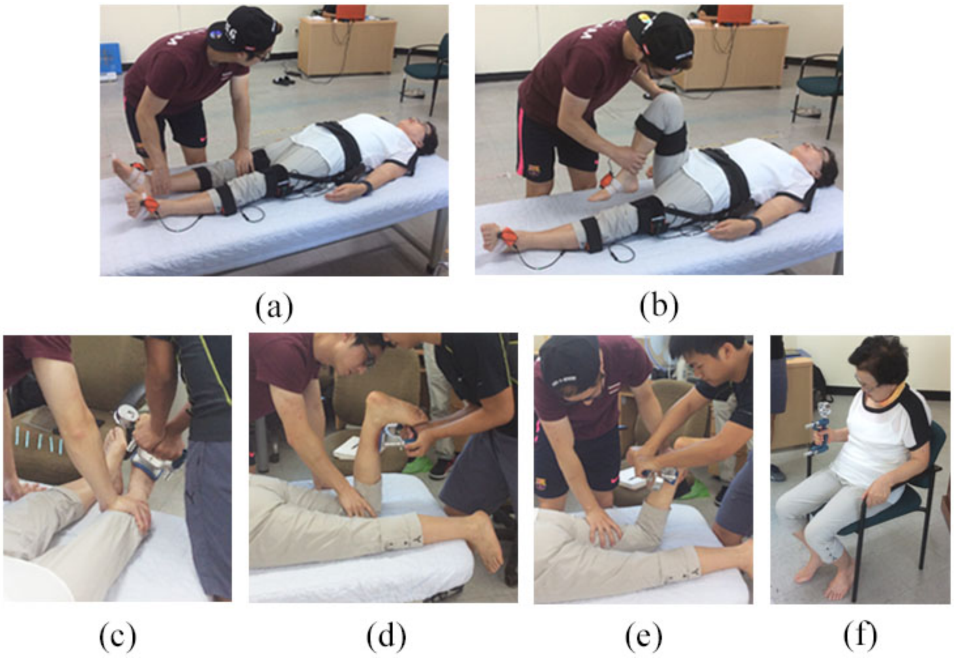


FIGURE 2.8: Experimental setting of motor function test. (a) Range of motion of knee extension; (b) Range of motion of knee flexion; (c) Maximal muscular strength of ankle dorsiflexion; (d) Maximal muscular strength of knee extension; (e) Maximal muscular strength of knee flexion; (f) Maximal hand grip strength.

2.3.6 Reaction test

We have developed a reaction test APP on iPad Mini for assessing the performance of the central nervous system in fall-related factors. The APP allowed a user to perform the following four different reaction tests (Figure 2.9) in the Hick paradigm. Those four reaction tests were in line with the traditional card-sorting tasks (Mahurin and Pirozzolo, 1993).

(1) One-choice reaction test: At the beginning of the test, the card is facing down by showing the back side of the card with a brick pattern in the card display box (upper section of the screen). During the test, once the card is facing up displaying as a red card, the subject has to tap choice reaction button with red color (lower section of the screen) as soon as possible.

(2) Two-choice reaction test: When the card is facing up, red card or blue card will appear randomly in the card display box at a random time. The subject has to tap choice reaction button which has the same color with the card's color.

(3) Four-choice reaction test: When the card is facing up, one random suit among four suits (hearts, diamonds, spades, and clubs) will appear in the card display box at a random time. The subject has to tap the choice reaction button which has the same type of suit with the card (Figure 2.10).

(4) Ten-choice reaction test: When the card is facing up, one random number among ten numbers (0, 1, 2, 3. . . .9) will appear in the card display box at random time. The subject has to tap choice reaction button which has the same number with the card.

Each reaction test consisted of ten random trials to account for variations as well as to minimize the possible bias from problematic trials during the test. In order to avoid the confounding effect from different moving distances during the tests, a fingerprint was shown on the screen as an initial position of the finger (Figure 2.9). The distance between the fingerprint and the center of the choice reaction region was fixed to be the same for all four reaction tests.

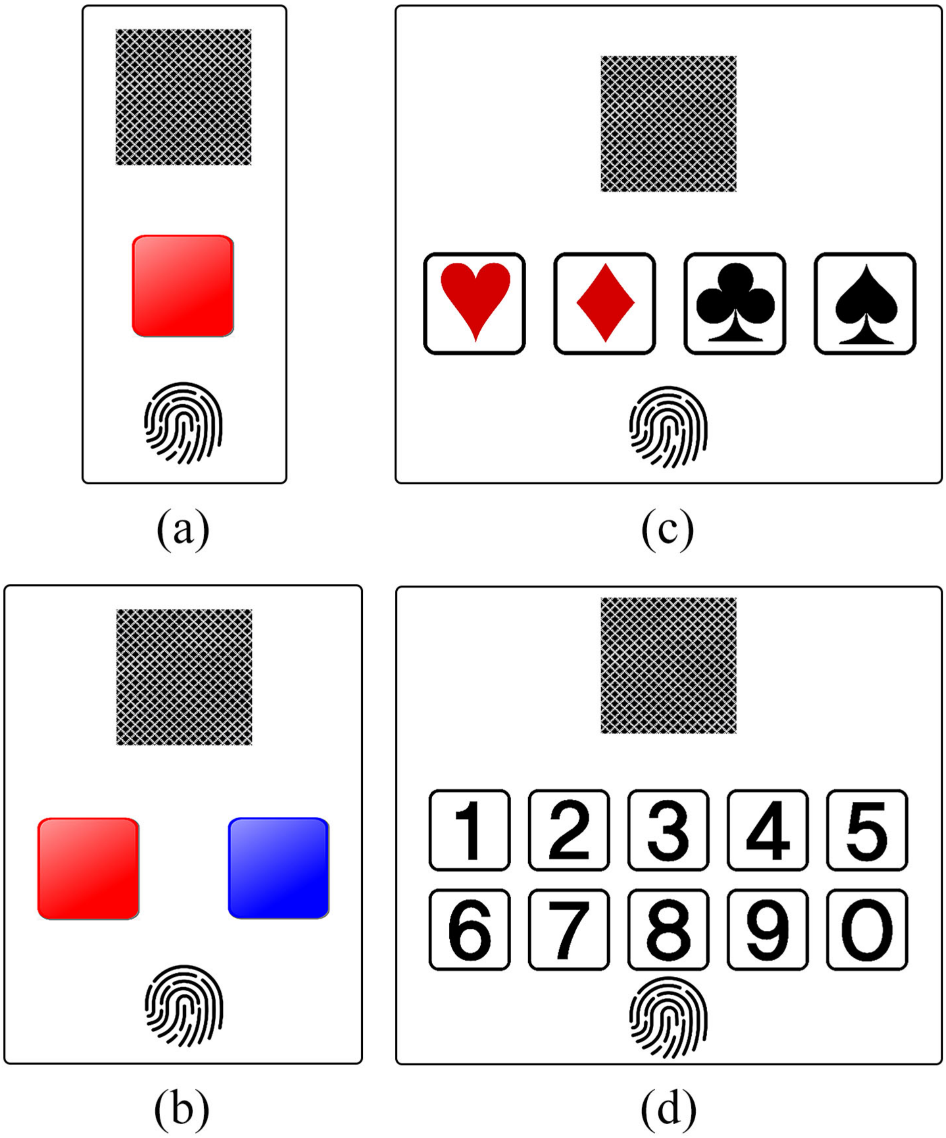


FIGURE 2.9: Interface design of four reaction tests in the developed APP. The upper section of each interface is the card display box (black brick pattern referred as card is facing down), the middle section is the choice reaction button (s) for the subject, and the lower section is a fingerprint where the participant puts the index finger at the beginning of tests. (a) One-choice test of red color; (b) two-choice test of red or blue color; (c) four-choice test of four suits (hearts, diamonds, spades, and clubs); (d) ten-choice test of 10 numbers from 0 to 9.

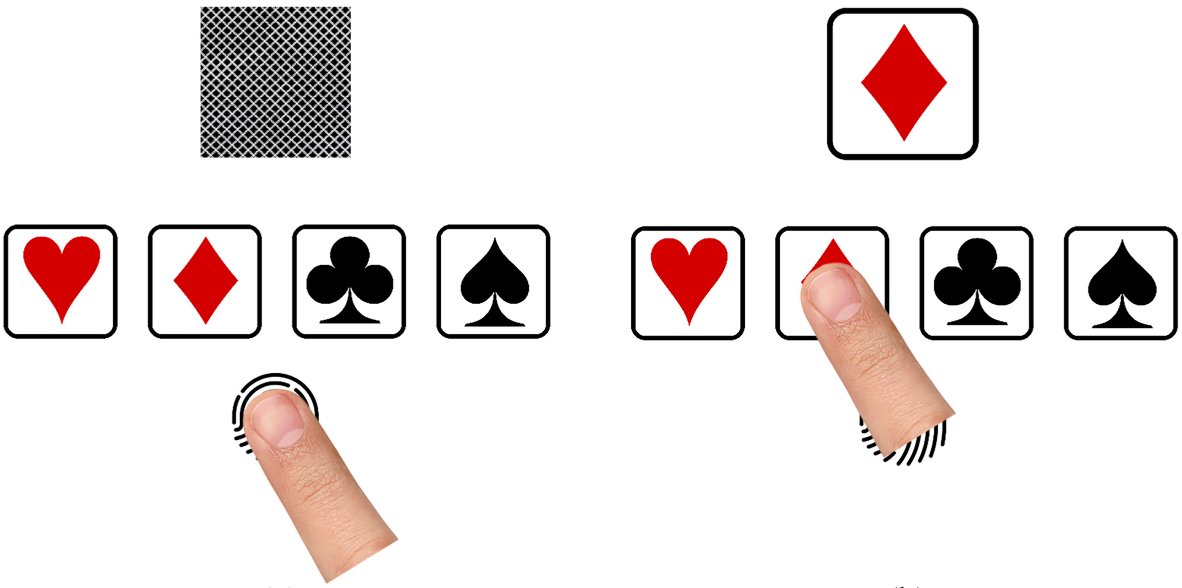


FIGURE 2.10: Demonstration of APP working mechanism with a four-choice test. At the beginning of tests, a subject puts the index finger at the fingerprint on the screen and the card is facing down with black brick pattern on it. During the test, the card is facing up with one random suit of four suits (hearts, diamonds, spades, and clubs) in card display box at a random time and the subject has to tap the choice reaction button which has the same type of suit with the card (diamond in the example). After one trial, the index finger would move back to fingerprint position and be ready for the next trial test.

2.3.7 Short falls efficacy scale international

The falls efficacy scale international (FES-I) is a self-report questionnaire, providing information on a level of concern about falls for a range of daily living activities. It was used to measure the fear of falling. The short FES-I (Table 2.1) is the short version of FES-I, and contains seven items scored on a four-point scale (1=not at all concerned to 4=very concerned) (Kempen et al., 2008). The short FES-I questionnaire was conducted through a face-to-face interview. The interviewer explained the meaning of items to participants and asked questions about how concerned they were about the possibility of falling while doing the activity. Participants should think about how they usually do the activity. If they currently don't do the activity (for example, if someone does shopping for them), they answer to show whether they think they would be concerned about falling if they did the activity. For each of the following activities, they have to check the box that is closest to their own opinion to show how concerned they are that they might fall if they did this activity.

TABLE 2.1: Items of short version of falls efficacy scale international.

		Not at all concerned 1	Somewhat concerned 2	Fairly concerned 3	Very concerned 4
1	Getting dressed or undressed	1 ☐	2 ☐	3 ☐	4 ☐
2	Taking a bath or shower	1 ☐	2 ☐	3 ☐	4 ☐
3	Getting in or out of a chair	1 ☐	2 ☐	3 ☐	4 ☐
4	Going up or down stairs	1 ☐	2 ☐	3 ☐	4 ☐
5	Reaching for something above your head or on the ground	1 ☐	2 ☐	3 ☐	4 ☐
6	Walking up or down a slope	1 ☐	2 ☐	3 ☐	4 ☐
7	Going out to a social event (for example, religious service, family gathering or club meeting)	1 ☐	2 ☐	3 ☐	4 ☐
	TOTAL SCORE=	*add all 1's*	*add all 2's*	*add all 3's*	*add all 4's*

2.4 Summary

In this section, we aimed to design a systematic and convenient test protocol for assessing fall risks and identifying the underlying causes of high fall risks. First, the different categories of tests were selected or developed based on the human balance and fall risk control system. Seven main tests were determined systematically to evaluate fall related factors, including a sensory integration test, limits of stability test, sit-to-stand five times test, timed up and go test, motor function test, reaction test, and short falls efficacy scale. Most tests were common, simple and easy to conduct in the practice. Additionally, we adapted inertial sensors as the main methods for data collection due to low cost and portability. In our experiment, the total time of all tests was within 30 minutes including 10 minutes for attaching and detaching sensors, and 20 minutes for the actual testing time.

Chapter 3

Validation of a reaction test APP based on Hick's law to assess cognitive function and fall risk in older people

3.1 Objective

In Chapter 2, we have developed a new reaction test APP as a part of the test protocol for fall risk assessment. A follow-up study was conducted in this chapter to examine the effectiveness of our develop reaction test APP on assessing cognitive function and fall risk in older people. The developed APP was tested on one hundred Korean women, consisting of twenty young controls, forty community-dwelling older non-fallers and forty matched older fallers. The movement time (simple sensorimotor response time) and information processing speed of each participant were derived through a log-linear regression of the reaction time on the number of alternative choices based on Hick's law. It was hypothesized that young people would show better cognitive functions than old people, and older fallers would demonstrate worse cognitive functions than older non-fallers.

3.2 Method

3.2.1 Reaction test APP development

In Section 2.3.6 of Chapter 2, we have developed an APP for iPad Mini using an iOS Apple language-Swift (Apple Inc.) that allows a user to perform four different reaction tests (Figure 2.9) in the Hick paradigm. The details of reaction test were also described. Reaction times of all test trials from APP were recorded and further utilized to derive two outcome measures (movement time and information processing speed) based on modified Hick's law (Roth, 1964):

$$Reaction\ time(RT) = Movement\ time(ie.A) + \frac{\log_2(n)}{Processing\ speed(ie., 1/B)}$$

, where n is the number of alternative choices. The recorded reaction times at the different numbers of choices from APP were subjected to a log-linear regression analysis, resulting in movement time (intercept A in the regression equation) and information processing speed (reciprocal of the slope B of the regression line) for each subject. Figure 3.1 shows three typical examples for a young people, an older non-faller and an older faller respectively.

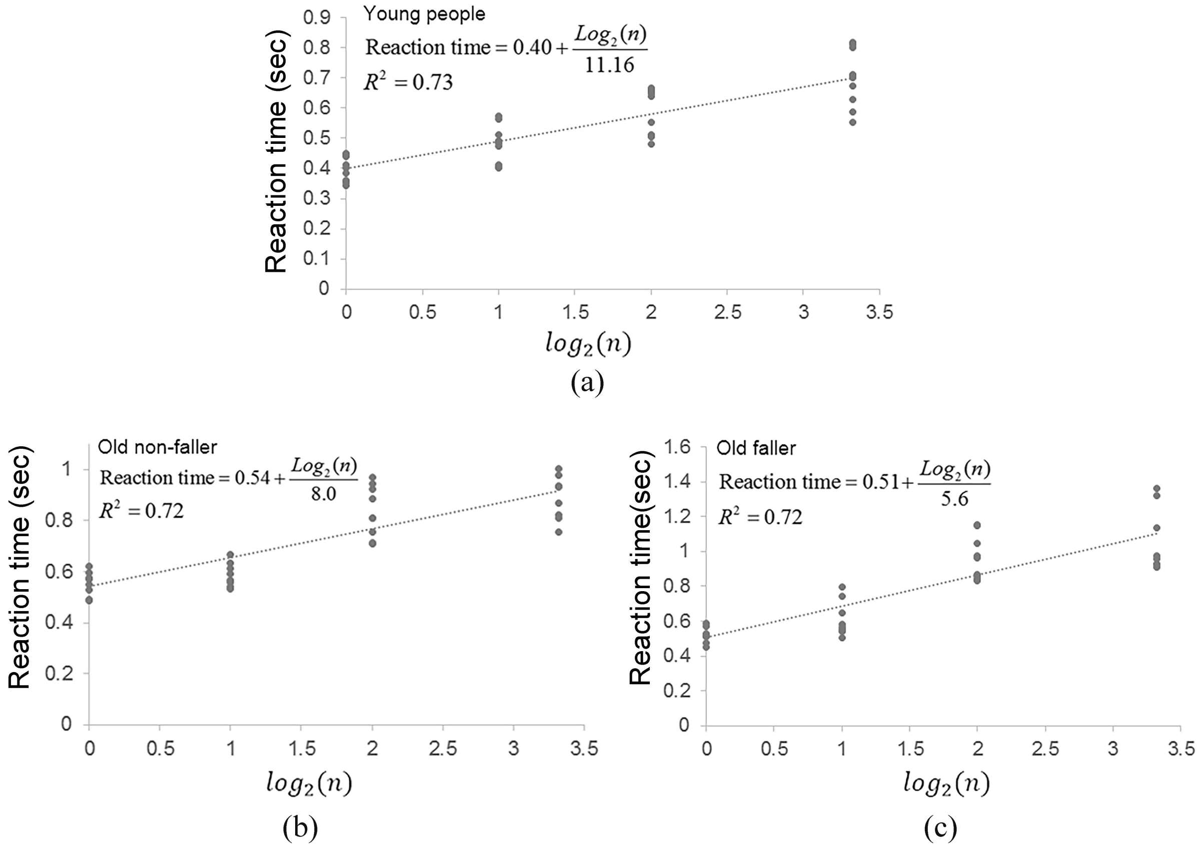


FIGURE 3.1: Typical examples of log-linear relationships between the reaction times and number (n) of alternative choices for a young people (a), an older non-faller (b) and an older faller (c).

3.2.2 Fall risk assessment with the developed APP

3.2.2.1 Experiment design and procedure

One hundred Korea women consisting of twenty young controls, forty community-dwelling older non-fallers and forty matched older fallers (Table 3.1), participated in the experiment. Based on a self-reported history of falling in the past 5 years, older people who had experienced multiple falls, or one fall requiring medical attention within one year prior to assessment, were categorized as ‘fallers’. Old participants were classified as ‘non-fallers’ if they did not fit into these criteria (Greene et al., 2012). A fall was defined as an unexpected loss of balance resulting in coming to rest on the floor, the ground, or an object below the knee level. No significant differences in age, height, and weight ($p > 0.05$) were found between older non-fallers and older fallers (Table 3.1). Only female subjects were recruited to avoid the potential gender effect on balance and fall risk control (Verghese et al., 2009). All subjects were right-handed and in healthy conditions with no self-reported neurological and musculoskeletal diseases or vestibular dysfunction that may affect their balance performance. Prior to the participation, each subject provided informed consent on a protocol approved by the university institutional review board (IRB No.14-32-A).

TABLE 3.1: Characteristics of experimental participants

Characteristics	**Young group (N=20)**	**Old group (N=80)**		
	Mean ± SD	Non-fallers (N1=40) Mean ± SD	Fallers (N2=40) Mean ± SD	p value of 2-sample comparison between non-fallers and fallers
Age (yrs)	22.45 ± 0.60	72.48 ± 4.36	71.75 ± 4.77	0.48
Height (cm)	160.78 ± 6.04	155.63 ± 5.46	153.91 ± 4.36	0.13
Weight (kg)	52.15 ± 5.67	58.27 ± 7.42	60.50 ± 7.56	0.19

A commercially available iPad Mini from Apple Inc., running the operation system iOS 8.1.3, was utilized in this study. It is an iOS-based mini tablet computer with 7.9 inches screen. Each participant was asked to sit on a standard chair with her left hand holding the iPad Mini and right hand taping the choice reaction button (s) at her comfortable posture. Prior to the test, practice session was conducted to make each participant be familiar with the experimental setting and procedure. During the test, each participant needed to complete ten random trials for all four reaction tests.

3.2.2.2 Data analysis

Two sample t-tests were performed on two outcome measures from the developed APP to compare the differences between the young and old groups (for age comparison), and the older faller and non-faller groups (for fall comparison). Since the decline of cognitive function and the increase of falls risk are significantly associated with ageing process, the ability to distinguish between age groups should be a necessary precondition for establishing the effectiveness of the developed APP on assessing fall risks. If the significance level of a certain outcome measure was reached for both age comparison and fall comparison, a follow-up Receiver Operating Characteristic (ROC) analysis (Greiner et al., 2000) would be carried out to examine the discriminative power of the specific measure on classifying fallers and to further determine the optimal cutoff value using Youden index (Fluss et al., 2005). Area under the ROC curve (AUC) was used to measure the discriminative ability. The general guideline of AUC is as follows (Hosmer Jr and Lemeshow, 2004): $AUC = 0.5$, no discrimination; $0.5 < AUC < 0.7$, poor discrimination; $0.7 < AUC < 0.8$, acceptable discrimination; $0.8 < AUC < 0.9$, excellent discrimination; $AUC > 0.9$, outstanding discrimination. MedCalc Statistical Software version 13.0 (MedCalc software bvba, Ostend, Belgium; `http://www.medcac.org/`; 2014) was used for statistical analysis and the significance level was 0.05.

3.3 Results

As shown in Table 3.2, the error rates of overall reaction tests were very small (<5%). In the data analysis, error data records were removed to increase the accuracy. As the number of choices increased, the reaction time increased. Elderly people showed long reaction time than reaction time than young people.

TABLE 3.2: Mean and standard errors of one-choice, two-choice, four-choice and ten-choice reaction time and error rate.

Group	*One-choice*	*Two-choice*	*Four-choice*	*Ten-choice*	*Error rate*
Young people	0.43 (0.012)	0.49 (0.011)	0.64 (0.014)	0.74 (0.016)	0.028 (0.0079)
Older non-fallers	0.59 (0.013)	0.77 (0.025)	0.98 (0.032)	1.15 (0.031)	0.047 (0.0054)
Older fallers	0.63 (0.019)	0.85 (0.023)	1.15 (0.035)	1.25 (0.034)	0.049 (0.0066)

Older people showed significantly longer movement time ($p < 0.0001$, Figure 3.2a) and slower information processing speed ($p < 0.0001$, Figure 3.2b) than the young control group. Within the old group, even though there was no significant difference between older non-fallers and fallers on the movement time ($p = 0.54$, Figure 3.3a), the older faller group had significantly slower information processing speed than the older non-faller group ($p < 0.0001$, Figure 3.3b). The follow-up ROC analysis (Figure 3.4a) and interactive dot diagram (Figure 3.4b) showed that the information processing speed had excellent discriminative ability ($AUC = 0.80$, (Hosmer Jr and Lemeshow, 2004)) on distinguishing older fallers and older non-fallers. The optimal cutoff value of information processing speed was 6.4 bit/second, resulting in overall classification accuracy of 78%, sensitivity (true positive rate) of 85% and specificity (true negative rate) of 70%.

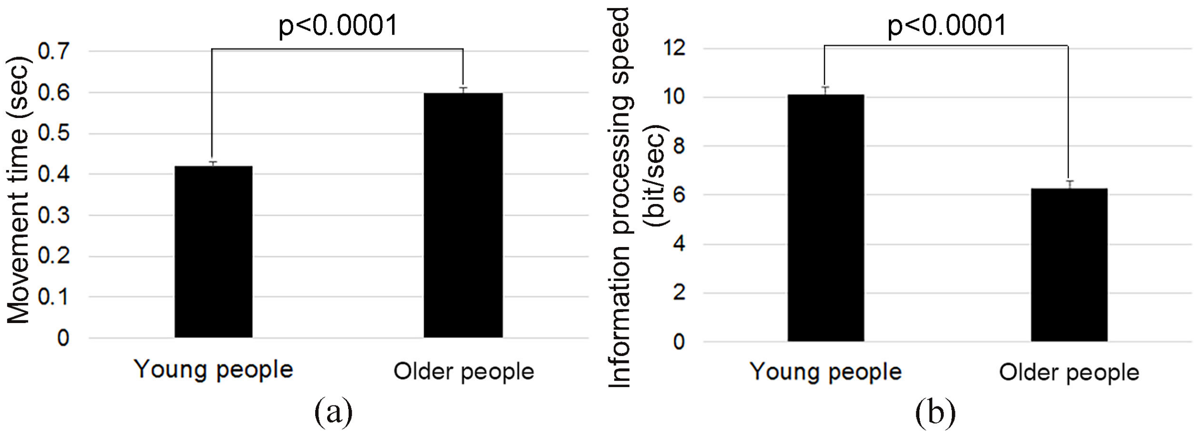


FIGURE 3.2: Mean and standard error of movement time (a) and information processing speed (b) between young and older groups.

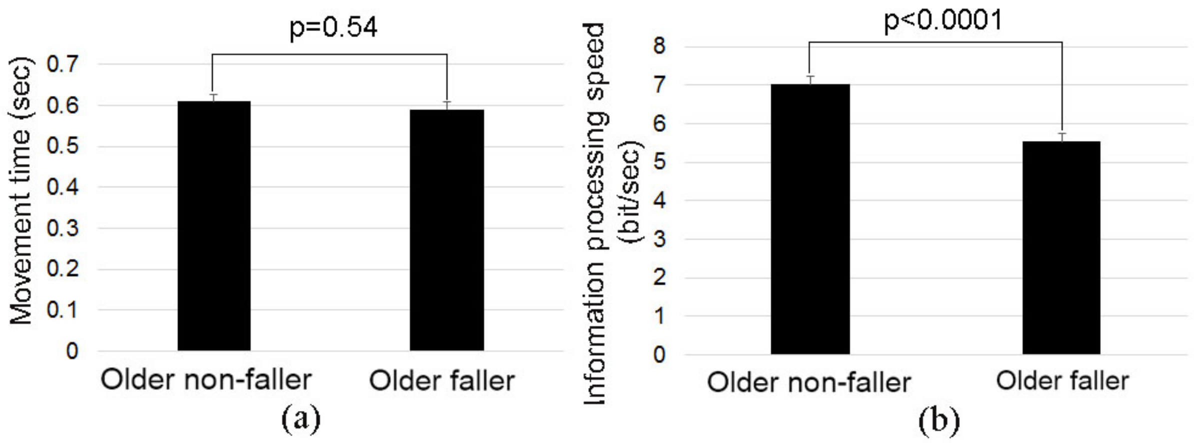


FIGURE 3.3: Mean and standard error of movement time (a) and information processing speed (b) between older non-fallers and older fallers.

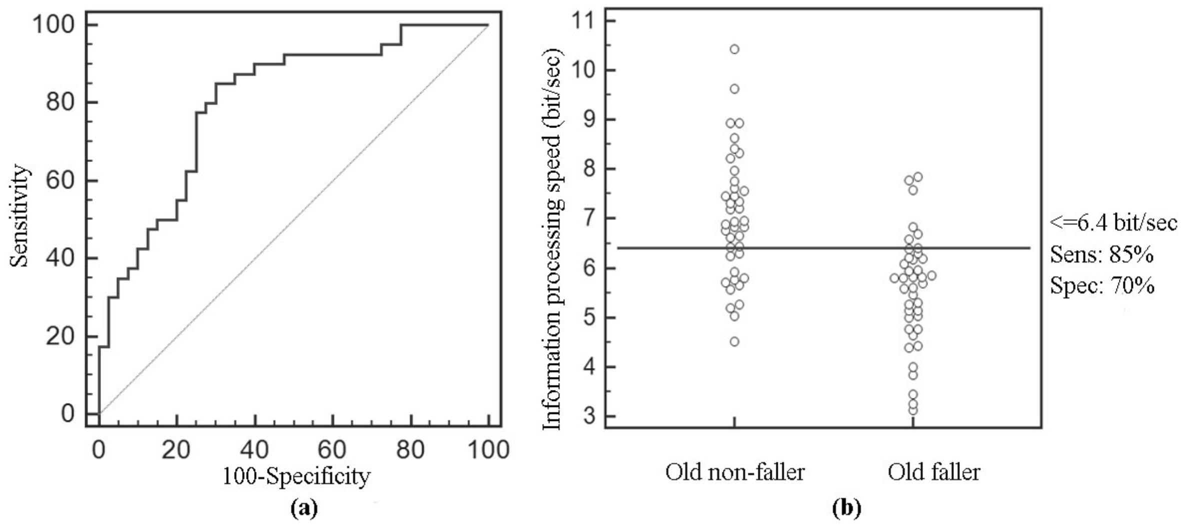


FIGURE 3.4: (a) receiver operating characteristic (ROC) analysis of information processing speed on classifying older fallers and older non-fallers. Area under ROC curve is 0.80. (b) interactive dot diagram of information processing speed for older non-fallers and older fallers. Sens: sensitivity; Spec: specificity.

3.4 Discussion

In order to investigate the potential use of reaction time for assessing cognitive function and falls risk in older people, we developed a reaction test APP based on Hick's law on iPad Mini. iPad Mini (7.9 inch) was chosen as the device to conduct the experiment for taking the advantage of the proper size compared with iPhone 6 (4.7 inches) and the convenience and portability compared with iPad (9.7 inches). Additionally, compared with the traditional card-sorting task timed by an experimental operator using a stopwatch, our tool has advantages when being used to measure the reaction time of the task in an accurate manner. Mahurin and Pirozzolo (1993) noted that there was a potential confounding between choice conditions and the amount of movement due to far distance when a subject physically placing cards in 10 piles from 1 to 10 in the traditional timed card-sorting task, so information processing time and movement time would be overlapped. However, with the developed APP and reaction test tasks, the distance was designed to be much shorter to minimize the effect of the distance. Furthermore, the reaction test through this APP can be considered time-effective (4 minutes in total from the onset of the test) and should be reliable as well since 10 random repetitions of each test were used.

This is the first study that utilizes APP to empirically measure movement time and information processing speed of older people for the purpose of assessing fall risks. The results showed that the outcome measure of information processing speed is not only sensitive to age related differences (young vs. old), but also fall risks in older people (older fallers vs. older non-fallers). For older people, slower information processing speed than the young group was expected since the cognitive function declines with the ageing process (Mahurin and Pirozzolo, 1993). More importantly, our results also showed that information processing speed of older faller group was significantly slower than older non-faller group. This finding revealed that cognitive processing speed of human CNS is an important fall risk factor for the older population, due to the sensory and motor components associate with it. Slow information processing speed can delay the sensory integration process and necessary motor responses to regain human balance from critical situations of balance perturbations (Horak, 1997). The finding was in line with many previous studies. Even though the SRT (Lajoie and Gallagher, 2004) and CRT (Woolley et al., 1997) tests involved more complicated motor responses such as extending and flexing the knee (Grabiner and Jahnigen, 1992), and stepping on the required region (Lord and Fitzpatrick, 2001), the older faller group had significantly longer reaction time than the non-faller group.

Information processing speed showed excellent discriminative power on classifying older fallers and older non-fallers ($AUC = 0.80$). Based on the optimal cut-off value of 6.4 bit/second, the use of a single measure of information processing speed can achieve overall classification accuracy of 78%, with sensitivity of 85% and specificity of 70%. The high sensitivity (85%) indicated that most of older fallers had information processing speeds slower than 6.4 bit/second, probably implying declines in the cognition and higher fall risks. This should be reasonable since cognitive resources are required in balance control and slow reactions of CNS could delay the sensory integration process and necessary motor responses from muscles and joints, and result in falls (Horak, 1997). The relatively lower specificity (70%) showed that even though the majority of the non-fallers have faster information processing speeds than the cut-off value, still quite a portion of non-fallers (30%) have slower information processing speeds. This could be explained by the possible compensation effects from good sensory and motor functions of some non-fallers (Perry et al., 2007; Salonen and Kivelä, 2012) on human balance and fall prevention even though there is mild cognitive impairment. Collectively, we could conclude that information processing speed slower than the cutoff value of 6.4 bit/second is an important risk factor associated with cognitive function for the falls in older people. Verghese et al. (2009) examined the validity of a cognitive test of walking while talking (WWT) in predicting falls in older individuals. They reported low sensitivity ($\leqslant$ 46%) but high specificity ($\geqslant$ 89%). Compared with WWT, our reaction test can achieve both high sensitivity (85%) and acceptable specificity (70%). Furthermore, this shows the hybrid use of different tests could have higher correct classification of older faller and non-fallers.

Our study not only proposes a useful measure (information processing speed) to assess fall risk, but also provides a simple, meaningful and portable tool which has good potential to be widely applied in the clinic or at home for assessing cognitive capacity and falls risk of the older population. The test tasks are simple and quick to administer within a few minutes. All older people in this study can complete the tasks correctly without difficulty. When all four tests have been completed, two quantitative measures including movement time and information processing speed can be presented. Since falls are multi-factorial phenomenon, identifying the people who have high risks of falling and the underlying reasons are essential for an older people to receive appropriate interventions for proactive fall prevention (Deery et al., 2000). If an older people whose information processing speed is slower than 6.4 bit/second, he/she would be classified as an individual with high risk of falling and one of the underlying reasons is cognitive deficit or impairment. Afterwards, corresponding intervention strategy could be adopted for fall prevention and the efficacy of such intervention on improving cognitive information processing can be further evaluated by the developed APP. Additionally, as the reaction test APP was developed on iOS operating system and would be available in the Apple Store, it can be installed on all portable devices from Apple Inc. including iTouch, iPhone, iPhone Plus, iPad Mini, iPad air, and iPad Pro. The APP also can be easily extended to a smart phone or tablet with Android operation system (Google Inc.) so that the developed APP could be not only used in the clinic but also be accessible by most people who own a smart phone or a tablet computer, enabling the APP to be widely utilized in daily life, especially considering nowadays smartphone and tablet computer are becoming popular, and half the adult population owns a smartphone.

Regarding another outcome measure of movement time, older people showed significantly longer movement time than the young group. This result is reasonable since ageing has been reported to be associated with the decline of muscular strength and degradation of motor functions (Lindle et al., 1997) and consequently, older people performed the movement slower than the young controls. Interestingly, there was no significant difference on movement time between older fallers and older non-fallers. In this study, the movement time corresponds to simple sensorimotor response time when performing fairly easy physical tasks (finger movement and press), healthy older people without self-reported musculoskeletal disorders recruited in this study did not need to exert much motor effort to perform the required tasks. Consequently, there may be not much difference on motor function while performing the designed test tasks within healthy older people regardless of their fall history, resulting in no significant difference on movement time between older non-fallers and older fallers.

This study has some limitations. First, information processing speed was used to measure the cognitive performance of older people on an easy visual decision-choice task, so it was assumed that older people can make the choices correctly. Second, the cut-off value of 6.4 bit/second on information processing speed was generated from older Korean women, it should be used with caution for other populations. Further studies should be carried out with larger sample sizes and in different settings for research results verification. Third, in the reaction test, different types of stimulus were used in the different choices, such as color differences in two-choice test, the number differences in ten-choice test. The stimulus may affect the reaction time. Future study can be done to evaluate the effects of stimulus on the reaction time. Last but not least, only retrospective falls were used in this study for classifying the older people into fallers and non-fallers. Considering an inherent limitation of inaccurate recalling of past falls (Lord and Fitzpatrick, 2001), prospective studies are needed to confirm the prognostic value of the developed APP for future falls in older people.

3.5 Conclusion

We have designed and developed the software for a reaction test based on Hick's law. The test can be run as an APP on Apple iOS mobile operating systems and provides the older individuals and health care professionals with a convenient assessment tool of testing cognitive capacity of older people who may be at high risk of falls, thereby reducing the number of fall accidents caused by inadequate cognitive processing from CNS. The effectiveness of the developed APP on assessing age related differences and fall risks in the older population has been demonstrated through an experimental study with a sample of twenty young women and eighty community-dwelling older women. Experimental results showed that the developed APP is not only sensitive to age related differences, but also fall risks in older people. Information processing speed derived from this APP had excellent discriminative power on classifying older fallers and non-fallers. The findings indicated that slow information processing speed is an important risk factor for falling in older people and the developed APP is potentially useful for assessing cognitive function and falls risk of older people.

Chapter 4

Development of models for fall classification in older people

4.1 Objective

In Chapter 2, we proposed a new test protocol for fall risk assessment. Later in Chapter 3, we validated the ability of a developed reaction test in the test protocol on classifying fallers and non-fallers. In this Chapter, we were going to describe a large-scale experimental study based on the new test protocol and to build fall classification models from the experimental data. The objective of this Chapter was to develop appropriate models for classifying fallers and non-fallers. First, physiological, psychological, and integrated functions of the human balance system were evaluated through the tests included in our newly designed protocol. Significant measures that could distinguish fallers and non-fallers were chosen from available measures, which were derived from tests in the protocol. Afterwards, typical statistical models were utilized to classify fallers and non-fallers such as logistic regression, classification and regression tree, etc. These models used significant measures as the independent variables and fall category (faller or non-faller) as the dependent variables. The accuracies of these models were then analyzed to identify their appropriateness on classifying fallers and non-fallers.

4.2 Method

4.2.1 Participants

One hundred ninety-five Korean old females consisting of 76 fallers and 119 match controlled non-fallers participated in this study (Table 4.1). Only female participants were recruited in the experiment in order to avoid potential gender differences while performing the tests (Butler et al., 2009). In addition, women are two or three times more likely to fall than man (Cook et al., 1982; Exton-Smith, 1997). Based on a self-reported history of falling in the past 5 years, older people who had experienced multiple falls, or one fall requiring medical attention within one year prior to assessment, were categorized as ‘fallers’. Old participants who did not fit into these criteria were classified as ‘non-fallers’ (Greene et al., 2012). A fall was defined as an unexpected loss of balance resulting in coming to rest on the floor, the ground, or an object below the knee level. The criteria used to recruit participants were 1) female; 2) age over 65 years old; 3) all participants were physically fit, functionally independent, and had no self-reported neurological, musculoskeletal deficits or vestibular dysfunction, and they could complete all tests in our new test protocol independently. In the questionnaire of fall history, the participants should report whether they had fall history or not in past five years. If they had fall experience, then they were requested to report how many time they fell and the reasons and place of each fall occurring were also needed. If the participants got injuries due to the fall, they had to report the details of the injuries and which body segments were damaged. The participants gave their informed consents to participate in the study, which had been previously approved by the university institutional review board (IRB No. 14-32-A).

TABLE 4.1: Comparisons of baseline characteristics in experimental participants.

Characteristics	*Non-faller (N=119)*	*Faller (N=76)*	*P value*
Age (years)	71.90 ± 54.52	72.13 ± 5.06	0.80
Height (cm)	154.82 ± 5.46	154.29 ± 5.26	0.49
Weight (kg)	58.04 ± 7.10	59.70 ± 6.67	0.11

4.2.2 Instruments

Xsens MVN inertial motion capture system (Xsens Inc.) with lower body solution module, including seven inertial sensors, was utilized for data collection. In our experiment, we only used five of these Xsens sensors to collect the data while participants performed sensory integration test, limits of stability, sit-to-stand five times, timed up and go test, and knee extension/flexion in motor function test. Inertial sensor is also called inertial measurement unit (IMU) consisting of accelerometers, gyroscopes, and magnetometers (Figure 4.1), which outputs 9 degree of freedom (DOF) raw data including 3D accelerations from accelerometers, 3D angular velocity from gyroscopes, and 3D magnetizations respectively. Additionally, the orientations were also derived from acceleration, gyroscopes, and magnetometers by using sensor fusion algorithms (Madgwick, 2010). Raw data of accelerations, angular velocities and magnetizations from IMU were collected at a sample frequency of 100Hz. In the experiment, sensors were attached on the body segments of the pelvis, left and right upper legs, and left and right lower legs (Figure 2.3).

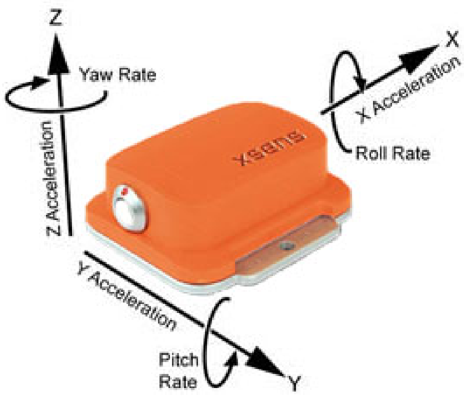


FIGURE 4.1: Typical example of an inertial sensor from Xsens Inc..

In our experiment, most of the measures were derived from inertial sensing data. Other measures can't be determined from sensing data were quantified by utilizing other simple methods. In the limits of stability test, yardsticks were attached to the wall to record the reach distances. A commercially available iPad Mini from Apple Inc. was utilized in the reaction test. A Jamar hand dynamometer was used to measure the maximal muscular strengthen while participants performed ankle dorsiflexion, knee extension and flexion, and hand grip. The questionnaire of short falls efficacy scale international was used to measure the fear of falling.

4.2.3 Experimental procedure

In the experiment, our newly designed protocol was implemented (the protocol was explained in detail in Chapter 2). The protocol contained seven main tests: sensory integration test, limits of stability test, sit-to-stand five times test, timed up and go test, motor function test, reaction test, and short falls efficacy scale questionnaire (Figure 4.2). The experimental procedure was presented in Figure 4.3. First, seven Xsens inertial sensors were attached on human body segments of the pelvis, two upper legs, two lower legs, and two foot. Then participants performed sensory integration test, limits of stability test, sit-to-stand five times test, timed up and go test, and knee extension and flexion in motor function test. After these tests, inertial sensors were detached from the body. Maximal muscular strengths of ankle dorsiflexion, knee extension and flexion, and hand grip in motor function were measured with a Jamar hand dynamometer. Participants performed the reaction test using an iPad mini. Finally, questionnaires of short falls efficacy scale international and fall history were completed through the face-to-face interview.

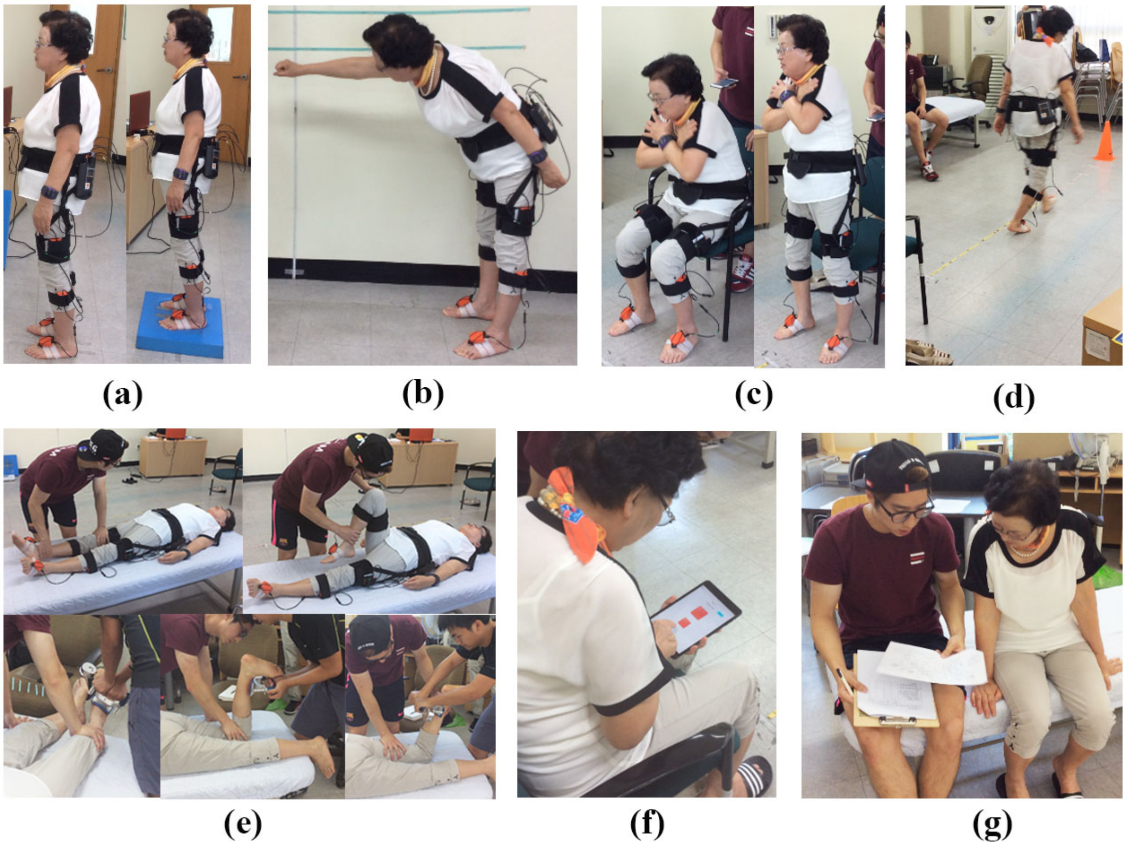


FIGURE 4.2: Seven tests in the test protocol: (a) sensory integration test; (b) limits of stability test; (c) sit-to-stand five times test; (d) timed up and go test; (e) motor function test; (f) reaction test; (g) the questionnaire of short falls efficacy scale international.

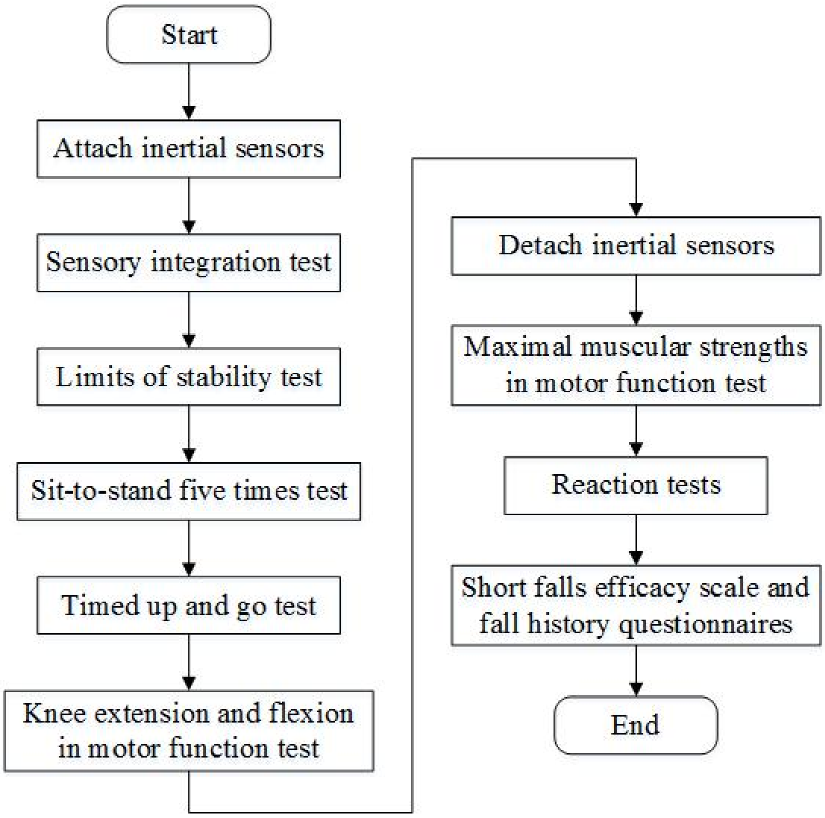


FIGURE 4.3: Overall experimental procedures.

4.2.4 Data processing

4.2.4.1 Overview of data processing

The data were collected and saved to the database while participants performed the tasks in the test protocol. Then these data in the database would be exported for post data processing and the algorithms to calculate different test based measures were developed.

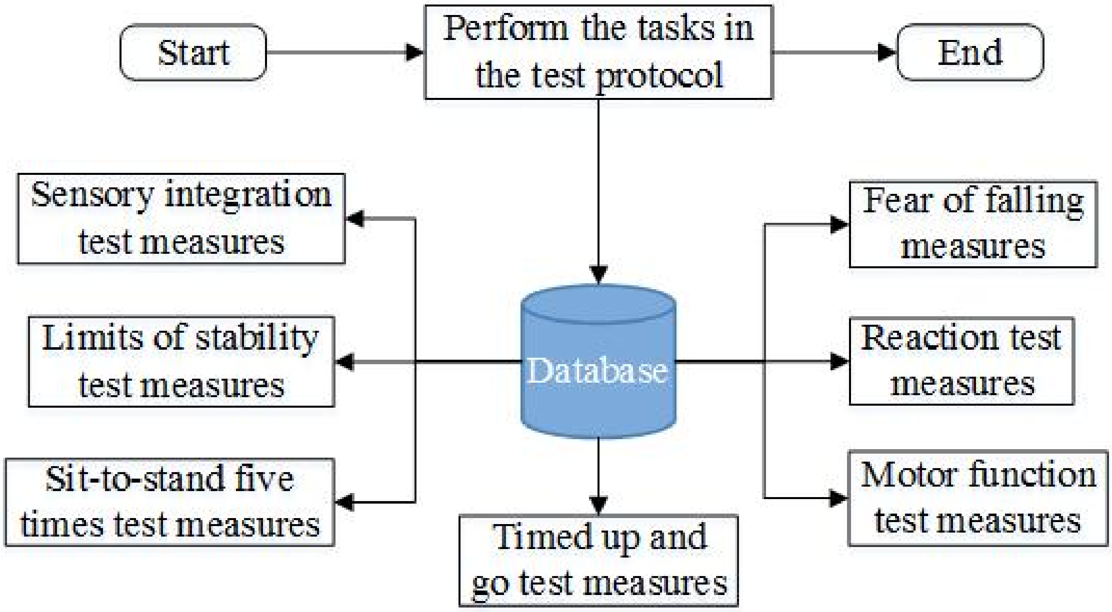


FIGURE 4.4: Overview of data processing.

4.2.4.2 Measures in sensory integration test

In sensory integration test, participants were required to stand as still as possible. During the posture was adjusted dynamically to react the gravity for achieving the balance. The sensor at the pelvis was most close to the center of body mass (COM). The pelvis sensor could reflect the movements of COM, so the data from the sensor at the pelvis were chosen to develop different types of measures for evaluating the postural stability. In the sensory integration test, measures could be classified into two types: test based measures that assessed the postural stability and sensory system based measures that assessed sensory system.

Test based measures were used to evaluate the postural control ability during quiet standing in different conditions and were derived directly from the raw sensor data. Generally, test based measures included time domain measures and frequency domain measures. Root mean square (RMS) and jerk of accelerations were found to be good measures on measuring postural stability (Mancini et al., 2011). RMS accelerations were parameters of the magnitude of raw data. Jerk was about the smoothness of acceleration change. Equilibrium score measured the range of tilt angles was also a good measure of postural stability. Hence, time domain measures included magnitudes of raw data, jerk, and tilt angle. Jerk is defined as the rate of acceleration changes, which is the derivative of acceleration with respect to time and the second derivative of velocity. In our measures, jerk of the acceleration is the derivative of the acceleration with respect to the time. Jerk of angular velocity is the second derivative of the angular velocity with respect to the time. In respect of tilt angle, equilibrium score (ES) was calculated by subtracting the difference between a maximum (θmax) and minimum (θmin) anteroposterior (AP) sway angle from the normal limit of the AP sway angle range, which is 12.5 degrees, and then divided it by the normal limit of the AP sway angle ranges, and multiplied it by 100. The following formula was used to calculate the equilibrium score:

$$Equilibrium\ Score = \frac{(12.5 - (\theta max - \theta min))}{12.5} \times 100$$

Figure 4.5 shows the example of the algorithm to calculate root mean square (RMS) accelerations in time domain measures. In the algorithm, time serials of accelerations in the anteroposterior (AP) direction from the sensor at the pelvis were used as the input data. The data were filtered, then were used to calculate RMS acceleration directly, and finally saved in the system.

In frequency domain measures, median frequency and power density spectral are the basic measures. In addition, centroid frequency was found to be a good measure of postural stability (Mancini et al., 2011). Thereby frequency domain measures include median frequency (MF), centroid frequency, and power spectral density of raw data. Figure 4.6 shows the algorithm to generate power spectral density of the acceleration. In the algorithm, accelerations and angular velocities through the time were used as the input and were filtered afterwards. Differences from time domain measures were that frequency domain data were derived from time domain data through using Fast Fourier Transform (FFT). Finally, power spectral density of the acceleration was calculated based on frequency domain data. All time and frequency domain measures were summarized in Table 4.2.

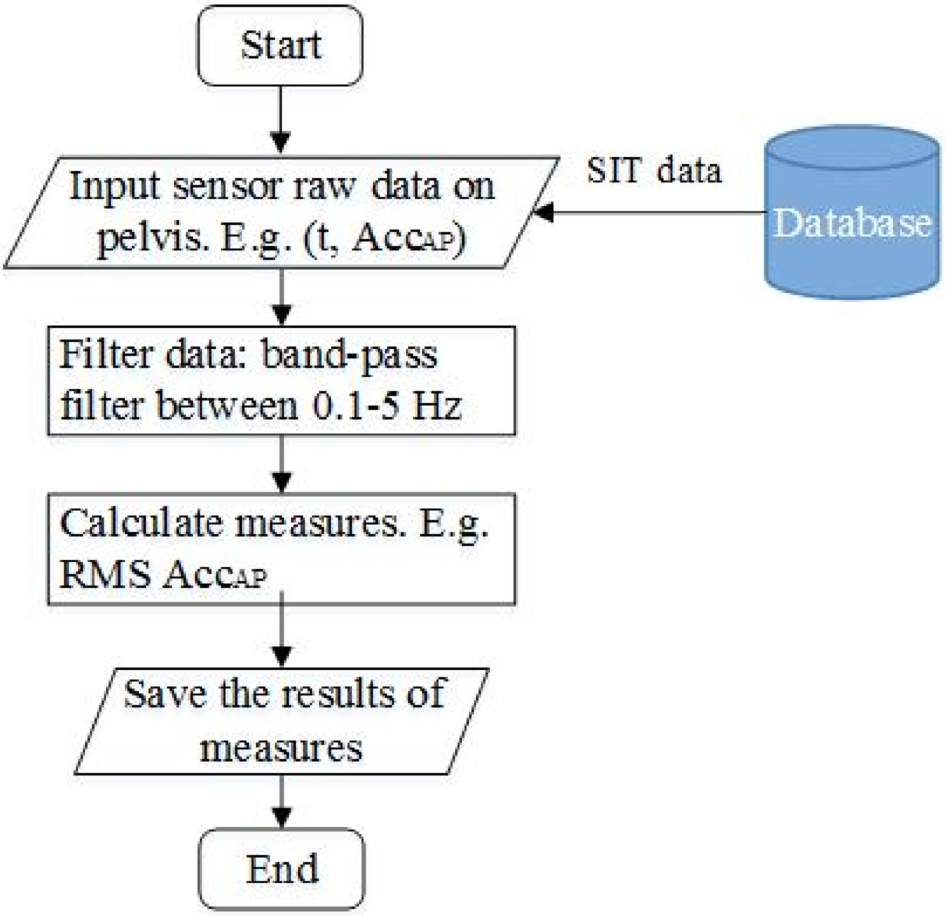


FIGURE 4.5: The algorithm of calculating time domain measures in sensory integration test. ACC: acceleration; AP:anteroposterior; RMS: root mean square.

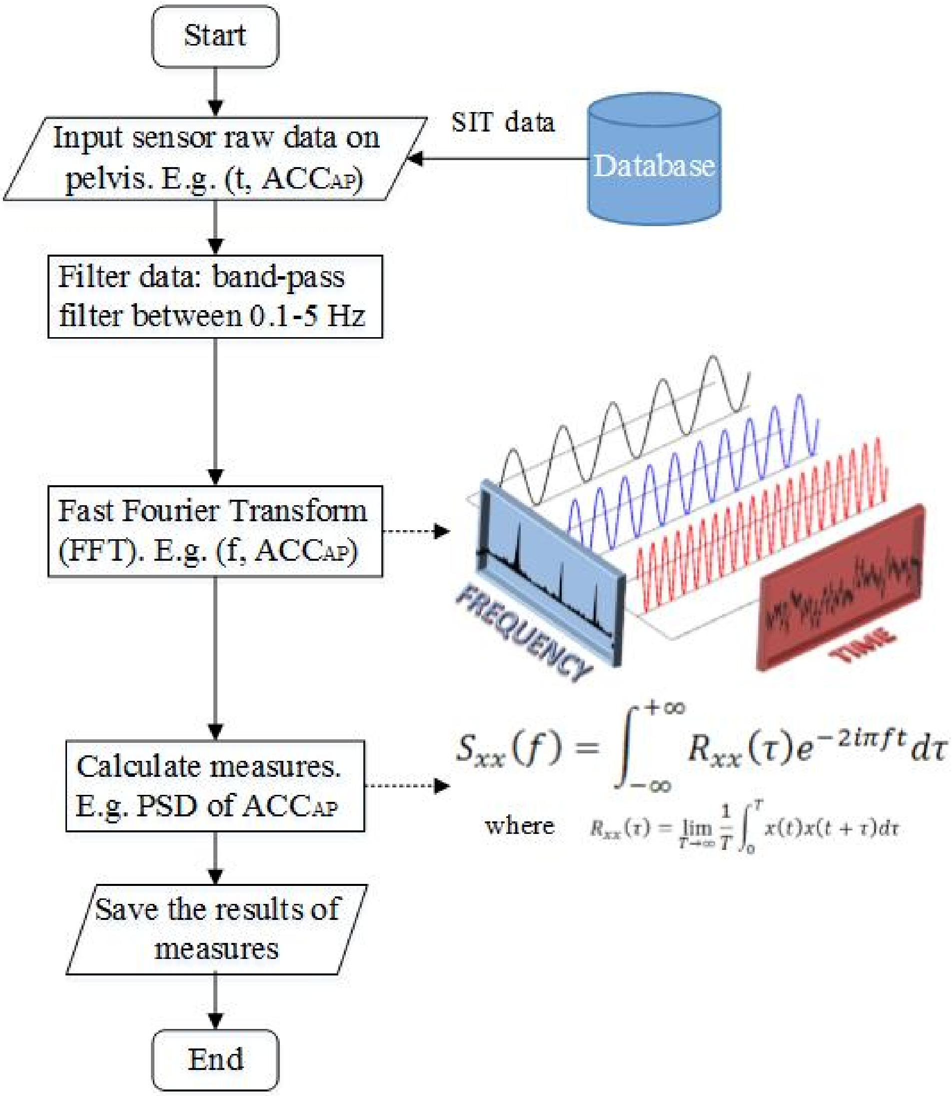


FIGURE 4.6: The algorithm of calculating frequency domain measures in sensory integration test. ACC: acceleration; AP:anteroposterior; PSD: power spectral density.

TABLE 4.2: Test based measures in sensory integration test. ACC: acceleration; angVel: angular velocity; AP: anteroposterior; ES: equilibrium score; ML: mediolateral; RMS: root mean square.

Category	***Subcategory***	***Measures***
Time domain	Magnitudes of raw data (ACC and angVel)	RMS ACC AP/ML
		RMS angVel AP/ML
	Jerk	RMS Jerk ACC AP/ML
		RMS Jerk angVel AP/ML
	Tilt angle	RMS ES AP/ML
Frequency domain	Median frequency (MF)	RMS MF ACC AP/ML
		RMS MF angVel AP/ML
	Centroidal freqency (CF)	CF ACC AP/ML
		CF angVel AP/ML
	Power spectral density (PSD)	PSD ACC AP/ML
		PSD angVel AP/ML

As the domain sensory systems on controlling balance varied as the test condition changed in sensory integration test, we could apply this pattern to generate the performance of each sensory system indirectly. Eliana et al. (2009) summarized the contributions of subsystems as

$$SOM = \frac{Cond2}{Cond1} \times 100$$

$$VIS = \frac{Cond3}{Cond1} \times 100$$

$$VES = \frac{Cond4}{Cond1} \times 100$$

where, Cond represented the condition.

In addition to individual sensory system, Balance Master Pro system proposed the equation to calculate composite equilibrium scores (CES) based on the measures. The equation is as follows (Baker, 2003):

$$CES = \frac{Avg(Cond1) + Avg(Cond2) + Cond3T1 + Cond3T2 + Cond4T1 + Cond4T2}{1+1+2+2}$$

where Avg, Cond, and T represented the average, the condition, the trial. Figure 4.7 showed the algorithms of calculating somatosensory (SOM), visual (VIS), and vestibular systems scores based on accelerations in AP directions. Time serials of the acceleration AP were input to algorithm and were filtered by a band-pass filter. RMS accelerations in 4 conditions would be calculated and then used to generate the SOM, VIS, and VES system scores. All sensory systems based measures were summarized in table 4.3

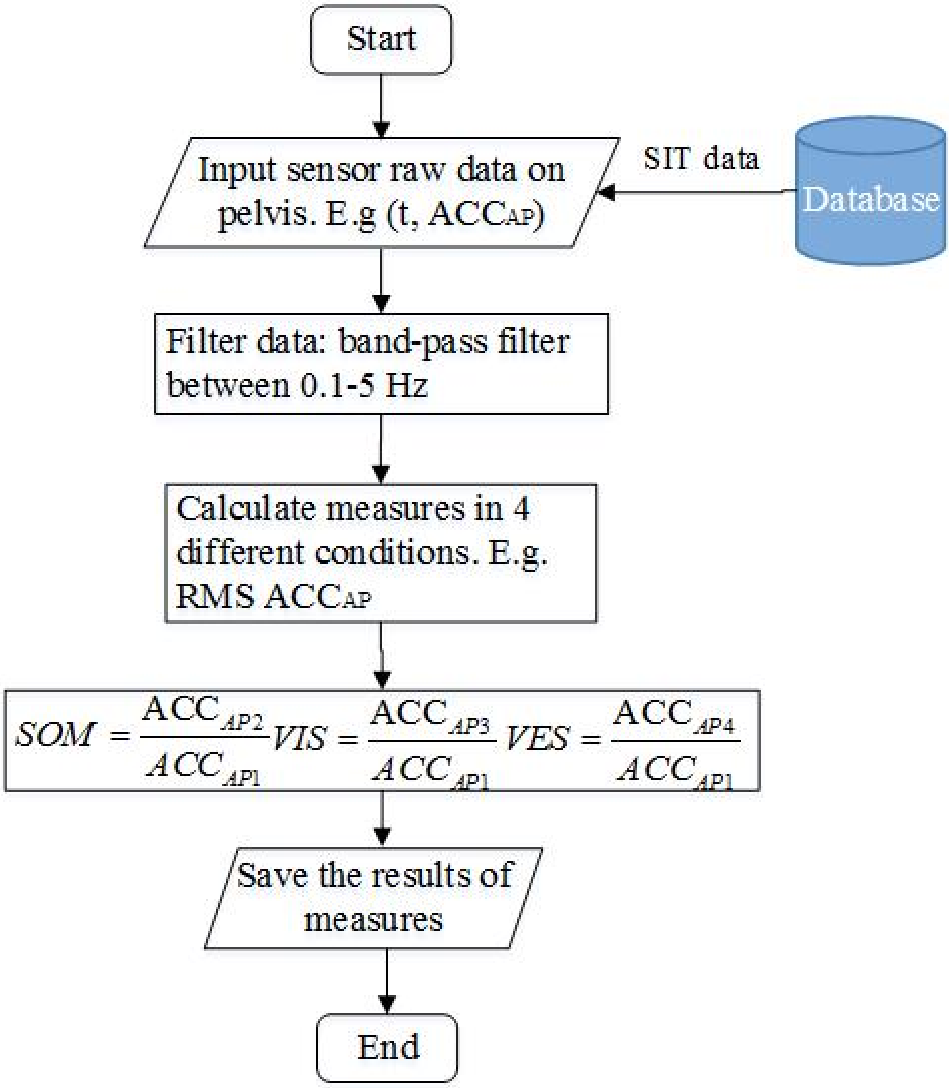


FIGURE 4.7: The algorithm of calculating sensory system measures in sensory integration test. ACC: acceleration; AP:anteroposterior; PSD: power spectral density. SOM: somatosensory; VES: vestibule; VIS: vision.

TABLE 4.3: Sensory system based measures in sensory integration test. ACC: acceleration; angVel: angular velocity; AP: anteroposterior; ES: equilibrium score; ML: mediolateral; RMS: root mean square; SOM: somatosensory; VES: vestibule; VIS: vision.

System	*Category*	*Subcategory*	*Measures*
SOM / VIS / VES / Composite systems	Time domain	Magnitudes of raw data (ACC and angVel)	RMS ACC AP/ML
			RMS angVel AP/ML
		Jerk	RMS Jerk ACC AP/ML
			RMS Jerk angVel AP/ML
		Tilt angle	RMS ES AP/ML
	Frequency domain	Median frequency (MF)	RMS MF ACC AP/ML
			RMS MF angVel AP/ML
		Centroidal freqency (CF)	CF ACC AP/ML
			CF angVel AP/ML
		Power spectral density (PSD)	PSD ACC AP/ML
			PSD angVel AP/ML

4.2.4.3 Measures in limits of stability test

In this test, the participants were asked to reach as far as possible. To do that, the participant's trunk was always bending during the test, so angular velocities from the sensor located in the pelvis were selected to generate measures. Since participants were asked to complete special tasks that were not easy for them, the RMS and jerk of angular velocity were used to measure difficulties while old people performed the tasks. In addition, we also applied the reach distance to measure the stability limits by using yardsticks. Additionally, in real situations of daily life, active reaches could mainly occur in forward, left and right directions but rare in the backward direction. Therefore, limits of stability (LOS) test included three directions functional reach: forward, left and right reach. Limits of stability contained reach distance, root mean square (RMS) angular velocity and RMS jerk angular velocity in forward, right and left directions. Figure 4.8 showed the algorithm to calculate RMS of angular velocity and jerk. First, the angular velocity and orientation on the pelvis from the database were input and filter. The start and end points of bending during functional reach are determined based on the pelvis orientation. In order to measure reach distance, The start point was recorded using the yardsticks on the wall before the participant executed functional reach test, while the end point was recorded when participants reached furthest distance. The reach distance equals to the difference between the start and end points on the yardstick. Finally, the RMS angular velocity and jerk during the reach can be generated. All measures in the limits of stability test are presented in Table 4.4.

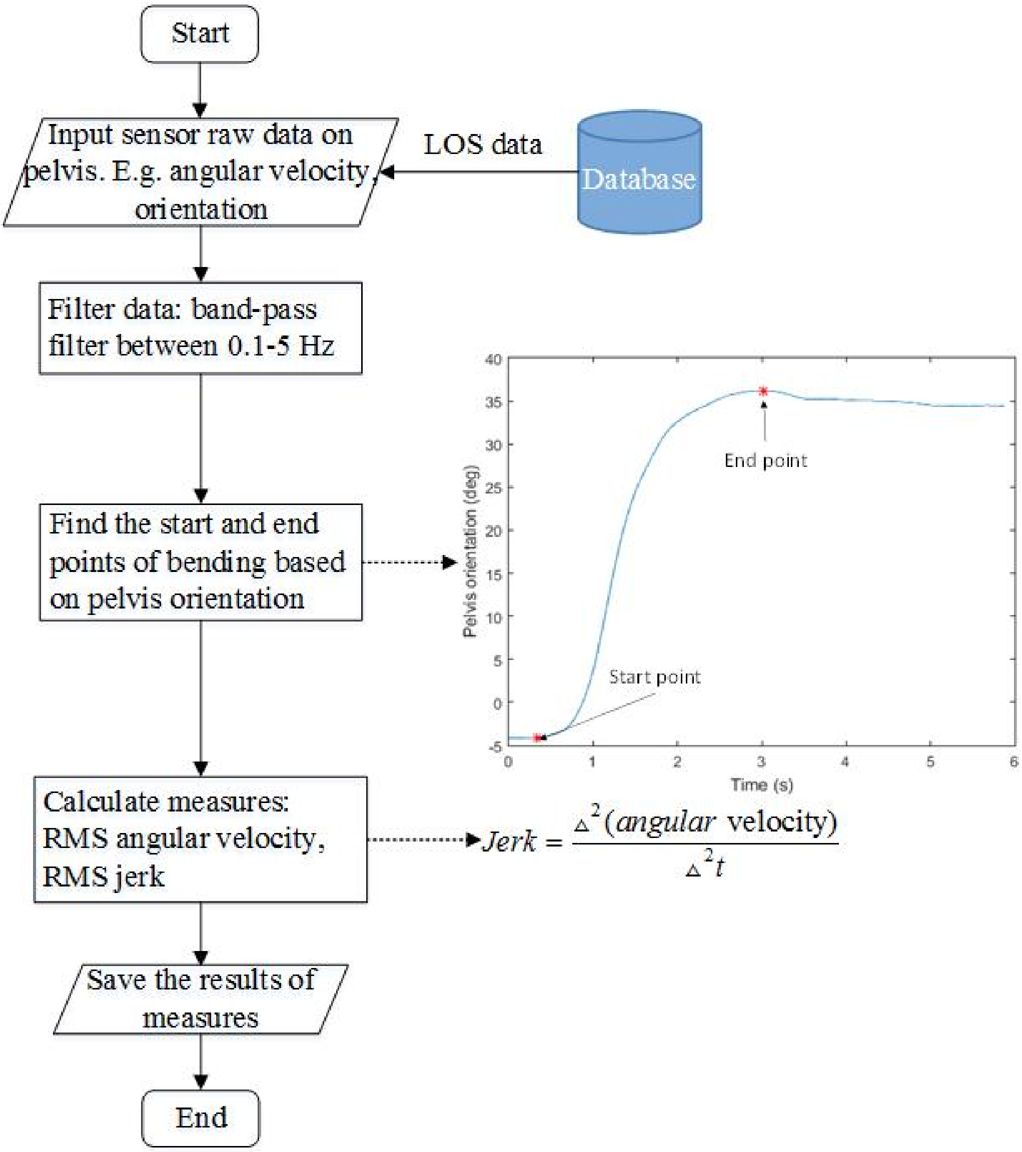


FIGURE 4.8: Sensor data processing in limits of stability test. RMS: root mean square.

TABLE 4.4: Measures in limits of stability. RMS: root mean square.

Functional reach direction	***Measures***
Forward reach	Reach distance
	RMS angular velocity
	RMS jerk
Right reach	Reach distance
	RMS angular velocity
	RMS jerk
Left reach	Reach distance
	RMS angular velocity
	RMS jerk

4.2.4.4 Measures in sit-to-stand five time test

In this test, the duration, RMS angular velocity and RMS jerk angular velocity were utilized to measure how difficult participants performed the task. So there were three types of measures derived in the period of a sit-to-stand process: sit-stand-sit measures, sit-stand measures, and stand-sit measures (Table 4.5). Each type contains the duration, RMS angular velocity and RMS jerk. The orientation and angular velocity from the sensor at the right upper leg were selected to derive the measures. Figure 4.9 shows the algorithm to calculate duration and RMS angular velocity during the period of sit to stand. In the algorithm, the orientation and angular velocity from the sensor at the right upper leg were selected as the input data and then filtered by a low-pass filter. The sit and stand points could be identified based on the orientation of the right upper leg. The duration and the RMS of angular velocity of sit to stand would be calculated. Sit-to-stand five time test measures were shown in Table A.10.

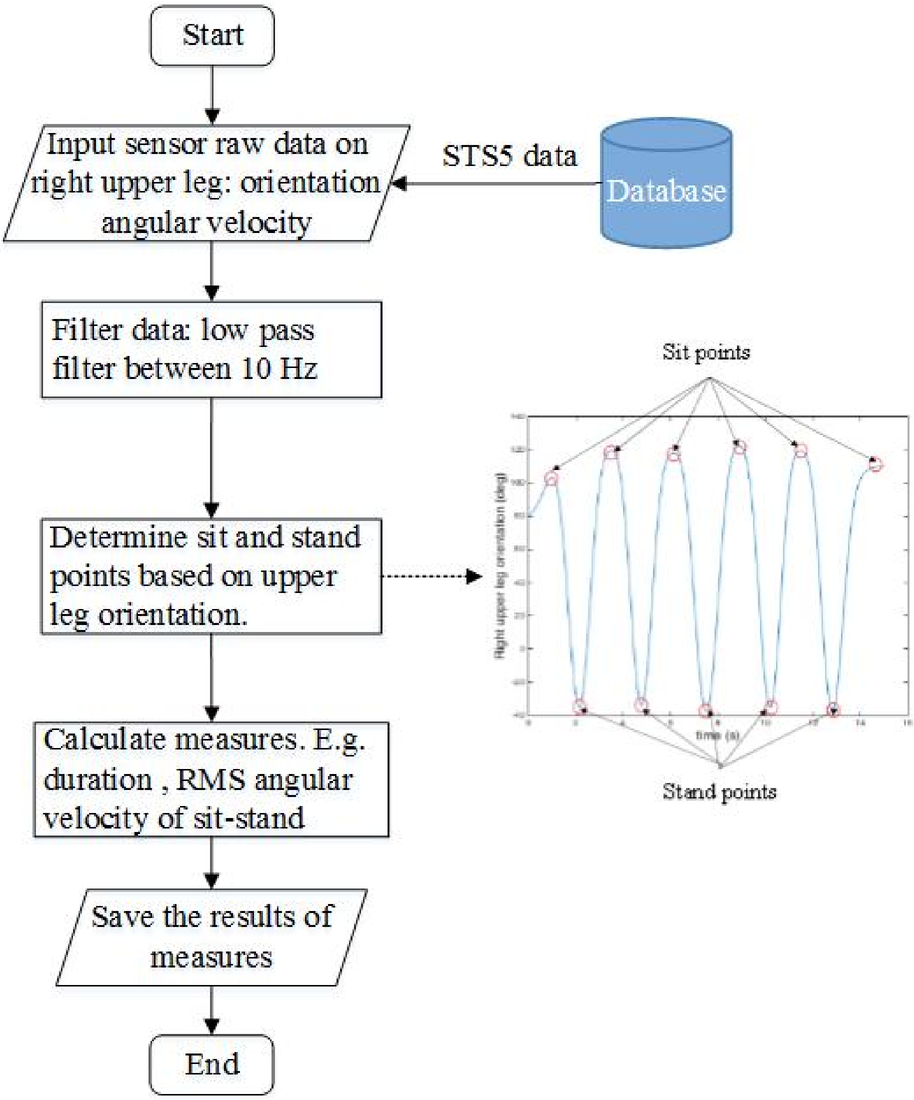


FIGURE 4.9: Sensor data processing in sit-to-stand five times test. in sit-to-stand five times test. STS5: sit-to-stand five times test .

TABLE 4.5: Measures in sit-to-stand five times test. RMS: root mean square.

Category	***Measures***
sit-stand-sit	Duration
	RMS angular velocity
	RMS jerk
sit-stand	Duration
	RMS angular velocity
	RMS jerk
stand-sit	Duration
	RNS angular velocity
	RMS jerk

4.2.4.5 Measures in timed up and go test

Many magnitude measures and gait pattern measures by using inertial sensors in timed up and go test showed the significant differences between fallers and non-fallers (Greene et al., 2010a). In addition, old people aged 65 or more showed significant turning difficulty (Thigpen et al., 2000). It was reasonable to have a hypothesis that fallers may show more turning difficulty than non-faller. The turning difficulty could be measured by the turning duration and angular velocity during turning.

Therefore, measures in timed up and go test can be classified into walking related measures and turning related measures based on the tasks. Walking related measures included magnitude measures and gait pattern measures (Greene et al., 2012). Magnitude measures were calculated by using acceleration and angular velocity from the sensor at the pelvis during walking. For the gait pattern measures , angular velocity from the sensors at the left and right lower legs were used to extract features. Figure 4.10 shows the algorithm to calculate magnitude and gait measures during the walking in timed up and go test. The angular velocity on pelvis and lower legs are input to the algorithm and are filtered by a low-pass filter. The angular velocity on lower legs are used to detect the toe off and heel strike during walking. These toe off and heel strike points are used to find the start and end points of walking for magnitude measures and can be also utilized to identify the gait cycle for gait measures such as the stride time. The range of the knee joint motion was calculated based on the orientations of upper and lower legs (Figure 4.11) and gait symmetric was also calculated based on range of the knee joint motion on left and right legs. In the turning measures, the turn period was determined by the magnetization and turning measures were calculated during this period (Figure 4.12).

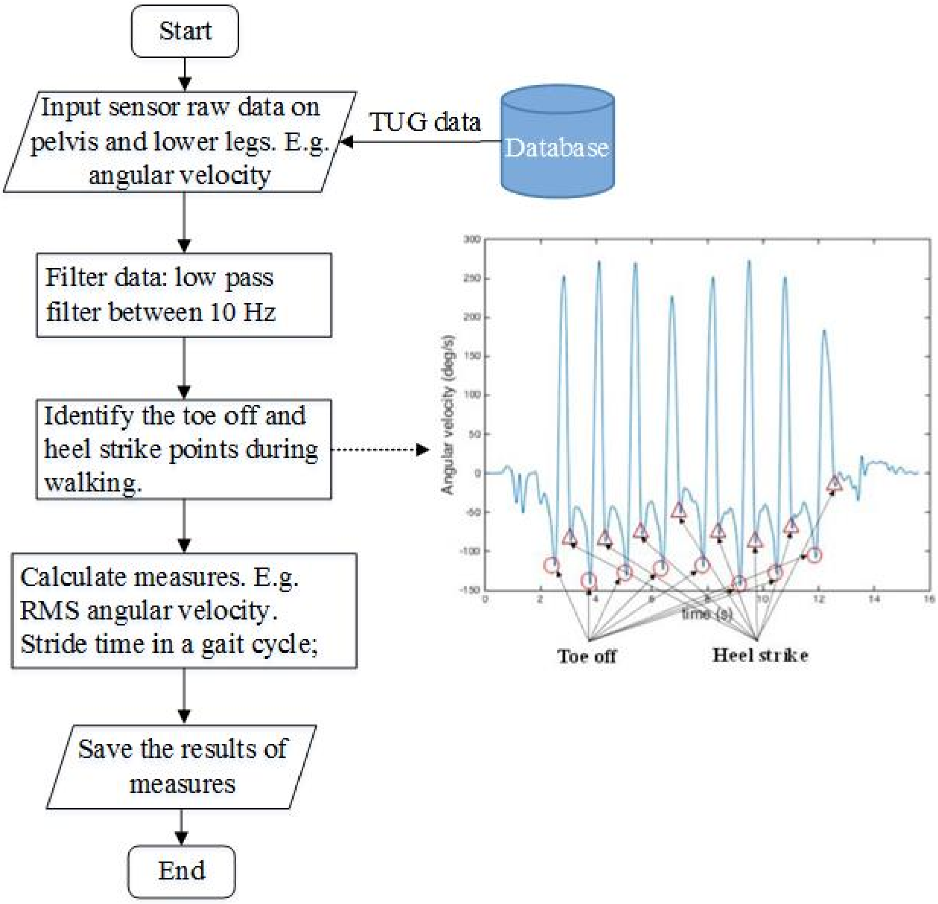


FIGURE 4.10: The algorithm of calculating magnitude gait measures in timed up and go test.

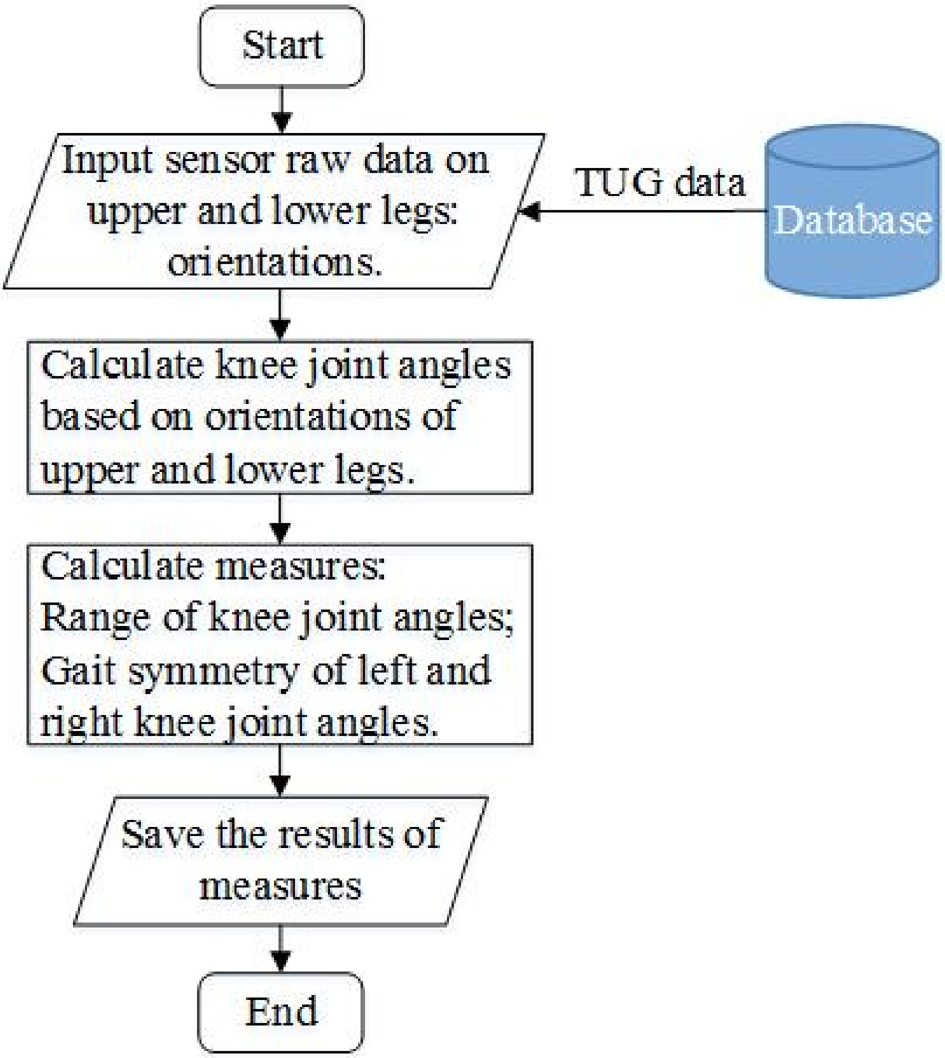


FIGURE 4.11: The algorithm of calculating range of motion measures in timed up and go test. TUG: timed up and go test.

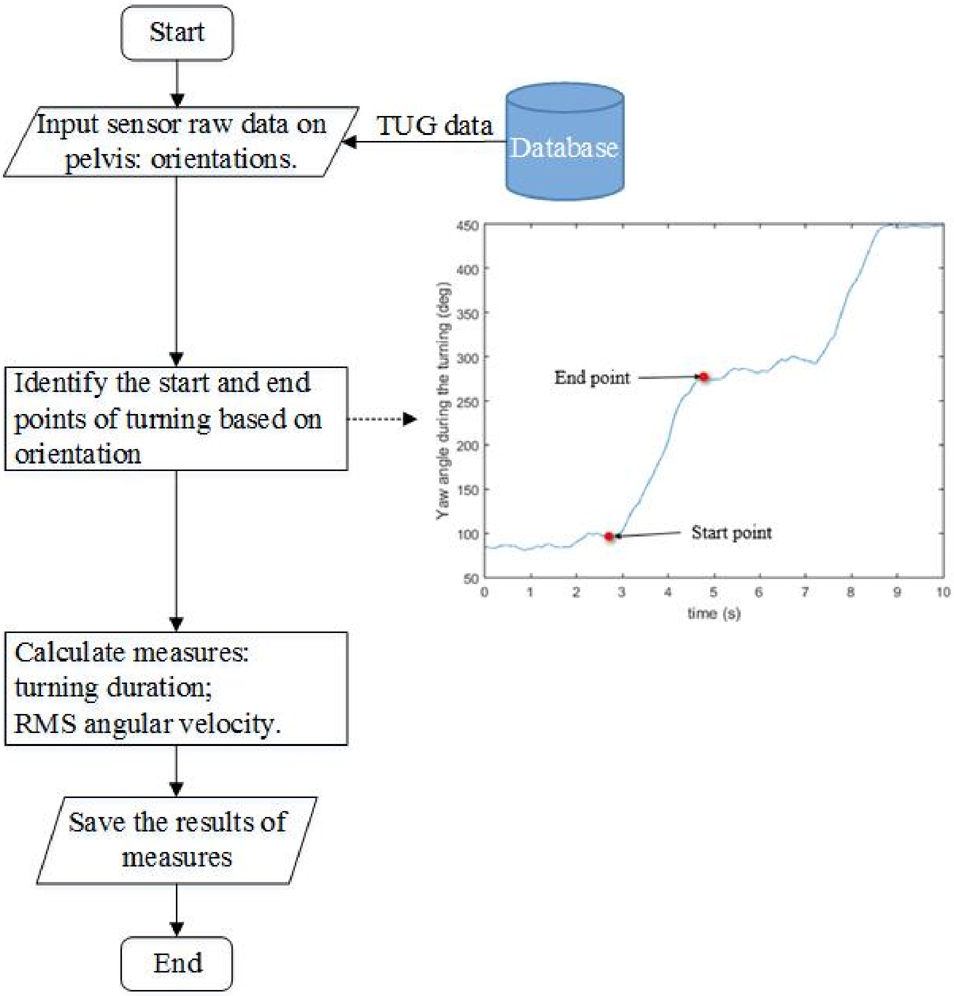


FIGURE 4.12: Calculates of turning measures in timed up and go test. TUG: timed up and go test.

TABLE 4.6: Measures in timed up and go test. AP: anteroposterior; ML: mediolateral; V: vertical; RMS: root mean square.

Phase	***Category***	***Measures***
Walking	Magnitudes of raw data	RMS acceleration AP
		RMS acceleration ML
		RMS acceleration V
		RMS angular velocity AP
		RMS angular velocity ML
		RMS angular velocity V
	Gait pattern	Gait velocity
		Stride time
		Stride length
		Single support
		Range of motion on knee joint
		Gait symmetry
Turning	Duration	Turning duration
	Magnitudes of raw data	RMS angular velocity
		Maximal angular velocity

4.2.4.6 Measures in motor function test, reaction test and fear of falling test

Motor function was assessed by considering the flexibility and maximum muscular strength (Figure 4.7). The flexibility was measured by range of knee extension and flexion. Similar with the range of motion of the knee joint, the orientations from the sensors at right upper and lower legs were utilized to calculate the knee joint angles. Then the ranges of knee joint angles during knee extension and flexion were calculated. The maximum muscular strengths were measured while participants performed ankle dorsiflexion, knee extension, knee flexion, and hand grip. In the reaction test, two measures including movement time and information processing speed were derived from four conditional tests based on the Hick's law. The short falls efficacy scale international (Short FES-I) score was generated after the participants completed the questionnaire.

TABLE 4.7: Measures in timed up and go test in motor function test

Category	***Measures***
Range of motion	Range of knee extension
	Range of knee flexion
Maximal muscular strength	Maximal ankle dorsiflexion force / weight
	Maximal knee extension force / weight
	Maximal knee flexion force / weight
	Maximal hand grip force / weight

4.2.5 Development of fall classification models

4.2.5.1 Introduction of typical classification models

In the theory of statistical learning, according to whether the data are labeled or not, the models are divided into supervised learning models and unsupervised learning models. In this study, our data were labeled as a faller or a non-faller based on fall history. So we intended to use supervised learning models to classify fallers and non-fallers. Many supervised learning models have been proposed for the classification. According to the flexibility of the model, these classification models include linear models, tree models, neural network models, and support vector machine (Friedman et al., 2001).

The basic linear model for classification is the logistic regression model, which is a regression model measuring the relationship between the categorical variable and one or more independent variables by estimating probabilities using a logistic function (Hilbe, 2009). In the logistic regression, the model tries to learn $p(y|x)$ directly that learns mappings directly from the space of input x to the labels y. It is also called discriminative learning model. There are also another kind of models called generative learning models, which try to model $p(x|y)$ by using the Bayes rule to derive the posterior distribution on y given x:

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)}$$

Linear discrimination analysis also called Gaussian discriminant analysis assumes that $p(\vec{x}|y)$ is a multivariate Gaussian distribution, where $\vec{x}$ is a vector of continuous variables. Another generative learning model is Naive Bayesion model that is also based on Bayes' theorem with independence assumptions between predictor variables.

Tree-based models partition the feature space into a set of rectangles, and then fit a simple model in each one. A popular and simple tree-based model is a classification and regression tree (CART). The basic tree models are easy to explain, more closely mirror human decision-making than do the regression and classification approaches, and are able to be displayed graphically. Unfortunately, basic trees generally do not have the same level of predictive accuracy. However, by aggregating many basic decision trees, using methods like bagging, random forests and boosting, the predictive performance of trees can be substantially improved. The boosted regression tree differs fundamentally from basic tree models (E.g. CART) that produce a single 'best' model, instead using the technique of boosting to combine large numbers of relatively simple tree models adaptively, to optimize predictive performance (Elith et al., 2008). Different from boosted tree model, random forests add an additional layer of randomness to bagging. In addition to constructing each tree using a different bootstrap sample of the data, random forests change how the classification or regression trees are constructed (Liaw and Wiener, 2002).

Neural network models in artificial intelligence are usually known as artificial neural networks (ANN). It is an information paradigm that is inspired by the way biological nervous systems, such as the brain, process information (Anderson, 1995). A neural network has several inputs, hidden, and output nodes. Each node applies a function (E.g. linear, logistic), and returns an output. Every node in the proceeding layer takes a weighted average of the outputs of the previous layer, until an output is reached. The reasoning is that multiple nodes can collectively gain insight about solving a problem (like classification) that an individual node cannot. The cost function differs for this type of model and the weights between nodes adjust to minimize errors. However, ANNs often converge on local minima rather than global minima, meaning that they are essentially "missing the big picture" sometimes, or missing the forest for the trees. ANNs often overfit if training goes on too long, meaning that for a given pattern, an ANN might start to consider the noise as part of the pattern.

Another advance model that overcomes the disadvantages of ANN is support vector machine (SVM), which is to construct a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks (Cristianini and Shawe-Taylor, 2000). In detail, SVM tries to fit a hyperplane/function between two different classes, while given a maximum margin parameter. This hyperplane attempts to separate the classes so that each falls on either side of the plane, and by a specified margin. There is a specific cost function for this kind of model which adjusts the plane until the error is minimized.

There is trade-off between prediction accuracy and model interpretability (James et al., 2014). Models with low flexibility such as logistic regression have good interpretability and low variance of its prediction accuracy, but low prediction accuracy and use restrictive assumptions. On the other hand, high flexible models such as SVM present high prediction accuracy but high variance of its accuracy and low interpretability. Therefore, we would like to select typical models with different flexibility. In this study, six typical statistical models including linear models of logistic regression and linear discriminant analysis, basic tree model of classification and regression tree, advance tree models of boosted tree and random forest, and support vector machine (SVM) radial basis function were used to assess the fall risk (Table 4.8).

TABLE 4.8: Typical fall risk assessment models.

Model type	**Typical model**
Linear Model	Logistic regression
	Linear discriminant analysis
Basic tree model	CART: Classification and regression tree
Advance tree model	Boosted tree
	Random forest
Support vector machine (SVM)	SVM radial basis function (SVMRBF)

4.2.5.2 Development of fall classification models

First, two-sample t-tests were performed on outcome measures from seven tests to compare the differences between the faller and non-faller groups. Cohen's effect sizes of t-tests for measures were also calculated. Cohen (2013) suggested the following guidelines for social sciences: $r = 0.1$ indicates small effect size; $r = 0.3$ indicates medium effect size; $r = 0.5$ indicates large effect size. Then a Receiver Operating Characteristic (ROC) analysis (Greiner et al., 2000) would be carried out to examine the discriminative power of the specific measure on classifying fallers and non-fallers. Area under the ROC curve (AUC) was used to measure the discriminative ability. Measures that were significant both on t-test and ROC analysis and effect size over than 0.3 were considered as the significant measures. The significance level of statistical analysis was 0.05.

Based on identified significant measures from each test, mathematical models were built to classify fallers and non-fallers. In this process, significant measures were selected as the independent variables of the models. The fall histories of the participants were used as the dependent variables of the models. After the models were constructed, cross validation was used to estimate the test error associated with a given statistical learning method to evaluate its performance and select proper level of flexibility. Available cross validation methods include leave-one-out cross-validation (LOOCV) and k-folder cross-validation. Here, LOOCV can be considered as the case of k=1 folder cross-validation. In this case, small k values always result to high variance and high running time. Larger k values mean less bias towards overestimating the true expected error. Here, LOOCV is always utilized when the training sample size is very small. In our study, we selected 10-fold cross-validation that was commonly used in previous studies (James et al., 2014). In 10-fold cross-validation, the original sample is randomly partitioned into 10 equal size subsamples. Among the 10 subsamples, a single subsample is retained as the validation data for testing the model, and the remaining 9 subsamples are used as training data. The cross-validation process is then repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data. The 10 results from the folds can then be averaged (or otherwise combined) to produce a single estimation. The statistical analysis, model constructions and accurate analysis were conducted in R using the caret package (Kuhn and Johnson, 2013).

4.3 Results

Table 4.9 summarized all significant measures from seven tests based on two sample t-test and AUC for simplified representation, the detailed results were attached in the Appendix A. In physiological function, in visual (VIS) system measures, fallers showed significantly higher root mean square (RMS) angular velocity anteroposterior (AP), jerk of acceleration AP and ML, jerk of angular velocity AP and ML, power spectral density (PSD) of acceleration mediolateral (ML) and angular velocity AP (Table A.1). In vestibular (VES) system measures, fallers had significant higher RMS angular velocity AP, jerk of acceleration AP and ML, power spectral density of acceleration ML and angular velocity AP, but lower equilibrium score (ES) ML than non-fallers (Table A.2). However, no somatosensory (SOM) system measures showed a difference between fallers and non-fallers (Table A.3). In the measures of overall performance of the sensory system (Table A.4), fallers showed significantly higher RMS acceleration AP and ML, RMS angular velocity ML, power spectral density of acceleration AP and ML and angular velocity of ML, but lower ES AP and ML than non-fallers. In central nervous system measures (Table A.5), fallers showed significantly lower information processing speed than non-fallers. However, there was no differences between fallers and non-fallers on movement time. In the motor function test (Table A.6), fallers showed the significantly smaller range of motion on knee extension and flexion non-fallers. The maximum muscular strengths of knee extension, flexion and hand grip of fallers were significantly smaller compared with non-fallers. In fear of falling test (Table A.7), fallers had significantly higher short falls efficacy scales international score than non-fallers.

In terms of integration function, in the postural stability measures, at the condition of eyes open and foam surface (Table A.8), fallers showed significantly higher RMS acceleration AP and ML, RMS angular velocity AP and ML, RMS jerk of acceleration AP and ML, RMS jerk of angular velocity AP and ML, power spectral density of acceleration AP and ML, and power spectral density of angular velocity AP and ML, and had the significantly lower equilibrium score AP and ML than non-fallers.

In limits of stability test (Table A.9), fallers showed significantly shorter reach distance and lower angular velocity and jerk in comparison with non-fallers during forward and right reach. For the left reach, fallers showed significantly shorter reach distance and jerk of angular velocity than non-fallers. During sit-to-stand five times test (Table A.10), fallers had a longer duration and slower angular velocity and jerk than non-fallers in the period of sit-stand-sit, sit-stand and stand-sit. In timed up and go test (Table

A.11), fallers had significantly lower RMS acceleration AP, RMS angular velocity AP, ML and V than non-fallers. In gait pattern measures, fallers had the significantly lower gait velocity, longer stride time, wider stride width and smaller range of motion on knee joints than non-fallers. During the turning, fallers showed significantly lower RMS and maximal angular velocity than non-fallers.

According to the experimental results of measures in seven tests, significant measures based on two-sample t-test and AUC were summarized in Table 4.9. These significant measures were used as the predictors of fall history. Then six typical models (Table 4.8) were built to assess the fall risks. Using 10-fold cross validation, the accuracies of models were shown in Figure 4.13. Among the models, SVMRBF, boosted tree and random forest had excellent accuracies (> 0.85). CART had good accuracy of 0.77 (> 0.75) but LDA and logistic regression had relatively low accuracies around 0.70. According to Gini variable importance in classification and regression tree model (Sandri and Zuccolotto, 2008), 10 most important measures were shown in Table 4.10.

TABLE 4.9: Summary of significant measures in seven tests. acc: acceleration; angVel: angular velocity; AUC: area under ROC curve; AP: anteroposterior; CES: composite equilibrium score; ES: equilibrium score; ML: mediolateral; PSD: power spectral density; FES-I: falls efficacy scale international; rms: root mean square; ROM: range of motion; V: vertical; VIS: vision; VES: vestibular.

Test	Significant measures
Sensory integration test (SIT)	SIT–postural stability: in eyes open & sway surface condition, rms acc AP and ML, rms angVel ML, jerk acc AP and ML, jerk angVel AP and ML, PSD acc AP and ML, PSD angVel ML
	SIT–VIS: rms angVel AP, ES ML, jerk acc AP, jerk acc ML, jerk angVel AP, jerk angVel ML, PSD acc ML, PSD angVel AP
	SIT–VES: rms angVel AP, ES ML, jerk acc AP and ML, jerk angVel AP, PSD acc ML, PSD angVel AP
	SIT–CES: rms acc AP and ML, rms angVel ML, ES ML, PSD acc AP and ML, PSD angVel ML
Limits of stability test	Reach forward: reach distance, jerk angVel AP
	Reach right: reach distance, rms angVel ML, jerk angVel ML
	Reach left: reach distance, jerk angVel ML
Sit-to-stand five times test	Sit-stand-sit: duration, rms angVel, jerk
	Sit-stand: duration, rms angVel, jerk
	Stand-sit: duration, rms angVel, jerk
Timed up and go test	Amplitude of raw data: rms acc AP, rms angVel AP, ML and V
	Gait pattern: gait velocity, stride time, stride length, single support
	Turning: maximal angVelV
Motor function test	ROM: knee extension, knee flexion
	Maximal strength: max knee extension, knee flexion, hand grip
Reaction test	Information processing speed
Fear of falling test	short FES-I score

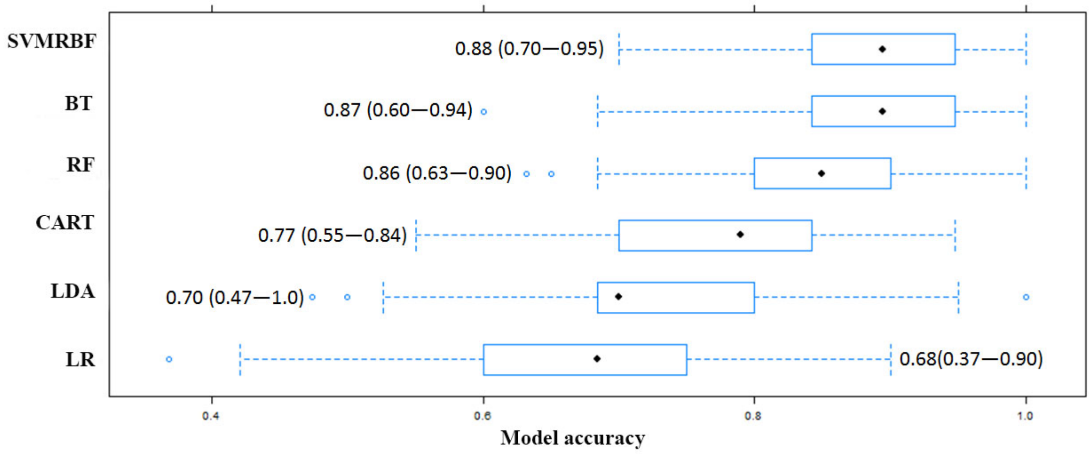


FIGURE 4.13: The accuracy of fall risk assessment models using 10-fold cross validation. BT: boosted tree; CART: classification and regression tree; LDA: linear discriminant analysis; LR: logistic regression; RF: random forest; SVMRBF: support vector machine radial basic function

TABLE 4.10: Top 10 importance measures based on the Gini variable importance in classification and regression tree. AP: anterioposterior; ML: mediolateral; FES-I: falls efficacy scale international; PSD: power spectral density; SIT: sensory integration test; TUG: timed up and go test; VIS: vision

Measures	*Overall score of Gini variable importance*
Information processing speed	38.1
Short FES-I	29.9
VIS PSD acceleration ML	17.6
VIS angular velocity AP	14.0
SIT PSD angular velocity AP	12.9
Sit-stand jerk	11.6
VIS PSD angular velocity AP	11.5
Sit-stand duration	11.4
TUG angular velocity AP	11.2
Maximal turning angular velocity	11.1

4.4 Discussion

4.4.1 Measures of fall related factors

In terms of physiological ability, fallers had the significantly higher angular velocity, jerk, and power spectral density than non-fallers in terms of the VIS system. For VES measures, fallers also had significantly higher angular velocity, jerk, and power spectral density, and lower equilibrium score than non-fallers. But none of the SOM system measures indicated the difference between fallers and non-fallers. As for composite measures, fallers showed significantly higher acceleration, angular velocity, and power spectral density, and lower equilibrium score than non-fallers. During sensory integration test, participants were required to stand as still as possible. The higher angular velocity, jerk, power spectral density, or lower equilibrium score indicated more movements during quiet standing, which was associated with the poor stability. Hence, fallers showed much weaker vision (VIS) and vestibule (VES) systems, and poorer sensory system compared with non-fallers. The findings were in line with previous studies. Vision played important roles in the balance control (Lord et al., 2003a). With the impoverished visual input, balance control and obstacle avoidance abilities became impaired due to misjudgment of distances and misinterpretation of spatial information. Impaired depth perception has been found to be among the strongest visual risk factors for multiple falls in community-dwelling older people (Ambrose et al., 2013; Salonen and Kivelä, 2012). Vestibular dysfunction was common in older people as a result of attrition of neural and sensory hair cells (Baloh et al., 2001). This often resulted in impairments in posture and gait, characterized by postural instability and a broad-based, staggering gait pattern with unsteady turns placing the older adult at an increased risk of recurrent falls (Sturnieks et al., 2008). Di Fabio et al. (2001) and Kristinsdottir et al. (2001) showed a relationship with increased risk of falls using more precise measurement of vestibular function. Shaffer et al. (2007) found that ageing caused impaired distal lower-extremity proprioception, vibration and discriminative touch in the somatosensory (SOM) system. Not all falls are resulted from lesions in the vestibular system. Many individuals experienced a sensation of disequilibrium or unsteadiness as a result of decreasing function in other sensory systems. A common cause of falls was a proprioceptive/somatosensory loss from peripheral neuropathy seen in diabetics and chronic alcoholics (Girardi et al., 2001). However, in our study, SOM-related measures showed no difference between fallers and non-fallers. The possible reason was that all participants were in good health condition even fallers.

In the reaction test, we found that fallers showed significantly higher information pressing speed than non-fallers, but there was no significant difference between fallers and non-fallers on movement time. Information processing speed was associated with cognitive function of central nervous system and movement time was related to the motor control in the reaction test. Impaired cognitive function was associated with increased fall risk (Muir et al., 2012). Information processing and reach time are important parts of cognitive function (Alexander and Hausdorff, 2008). Fallers showed the significantly short reaction time in simple reaction test and choice reaction test (Lord and Clark, 1996; Lord and Fitzpatrick, 2001). Fallers also had significantly poorer motor coordination skills in terms of lower joint flexibility and maximal muscular strength compared with non-fallers. The flexibility was measured by ranges of motion of knee extension and flexion. Greater flexibility was more useful on balance control. Lower ranges of motions were found to be associated with increased fall risk (Kerrigan et al., 2001; Tinetti et al., 1993, 1986). Muscle strength should be one important factor that were assessed and treated in older adults at fall risks (Moreland et al., 2004) and weak muscles were associated with high fall risks (Horlings et al., 2008). In the psychological aspect, fallers had significantly higher short falls efficacy scale international score than non-fallers. It indicated that fallers showed much higher fear of falling than non-fallers. The fear of falling has been identified as one of the key symptoms of 'past-fall syndrome' (Legters, 2002). The study of Legters (2002) also showed that 50% to 60% of reported fallers experienced fear of falling in several community samples. Fallers also showed significantly higher falls efficacy scale scores than non-fallers (Delbaere et al., 2010; Friedman et al., 2002).

In terms of integrated functions, in the sensory integration test, fallers showed significantly higher accelerations, angular velocities and jerks compared with non-fallers. Higher accelerations, angular velocities and jerks indicated unstable status when the test requires participants to stand stable as possible. So fallers showed poor postural control ability compared with non-fallers. Our findings matched those observed in earlier studies. Greene et al. (2012) found that fallers had significantly higher root mean square (RMS) acceleration and angular velocity than non-fallers during eyes open and closed on a firm surface. O'Sullivan et al. (2009) also found that fallers had significantly higher RMS acceleration than non-fallers during eyes open on the foam mat. From the frequency domain measures, fallers had significantly higher power spectral density than non-fallers. It demonstrated that fallers should take more effects to perform the same tasks compared with non-fallers.

In the limits of stability test, sit-to-stand five times, and timed up and go test, faller showed significantly slower accelerations, angular velocities and jerks. In these tests, participants were required to complete special tasks. The higher accelerations, angular velocities or jerks indicated that participants could perform the tasks faster and easier. Fallers had some difficulties on performing these tasks compared with non-fallers. Doheny et al. (2011) found that fallers had significantly lower total jerk than non-fallers during sit-to-stand five times test. Meanwhile, fallers also took longer time to perform the sit-to-stand five times test, timed up and go tests. In addition to the sensor raw data of acceleration and angular velocity, feature measures were also extracted from the acceleration and angular velocity in sit-to-stand five times test and timed up and go test. In sit-to-stand five times test, fallers took longer duration to complete the sit-to-stand five times test compared with non-fallers. Doheny et al. (2011) also found that mean of sit-stand duration fallers were significantly longer than non-fallers. In the timed up and go test, gait pattern measures were also extracted from the angular velocity of lower legs (Greene et al., 2010a,b). Fallers showed significantly lower gait velocity, longer stride time and shorter stride steps than non-fallers. While doing the turning movement, fallers took significantly longer time but smaller angular velocity than non-fallers. Greene et al. (2010a) found that fallers spent significantly longer walking time and stride time than non-fallers.

4.4.2 Fall classification models

In order to assess fall risk, our study covered the tests systematically that were associated with different aspects of balance control, which was measured by inertial sensors in most of the tests. Most previous studies (Seeing Table 4.11) only used some tests to build the classification models for assessing the fall risks, such as postural stability in quiet standing (Greene et al., 2010a), timed up and go test and 20-meter walking (Marschollek et al., 2011a,b), a directed-routine movement test consisting of a timed up and go test, a sit-to-stand five times test, and an alternate step test (Liu et al., 2011). As falls could be caused by many different factors, some tests only associated with parts of balance functions might not reflect the real reasons of falls. Systematic factors from different aspects could have more advantages on improving the accuracy of a model. For example, Marschollek et al. (2009) utilized two models to assess fall risks, where model 1 only used clinical assessment data consisting of Stratify score and Barthel index while model 2 added the sensor data from timed up and go test. Their results showed the accuracy of model 1 increased from 83.6% to the model 2 accuracy of 90%.

Our study applied the 10-folder cross validation to assess the accuracy of models for the model selection. In previous studies, many models were proposed to assess fall risk by using inertial sensors. A review study (Howcroft et al., 2013) reported half of geriatric fall risk research paper used derived models instead of correlating a variable with fall risk. However, 50% of these did not employ cross validation to evaluate the performance of their models. Thereby it limited the model's applicability beyond the train population. Due to the differences of evaluation methods, the model accuracy was also different. So we intended to compare the accuracy of models using the similar cross validation methods. Liu et al. (2011) and Caby et al. (2011) used leave-one-out cross-validation and Marschollek et al. (2011a; 2011b) and Greene et al. (2012) used ten-folder cross-validation for evaluating the fall classification model performance.

In the previous studies (Seeing Table 4.11), the frequently used classification models were logistic regression (Marschollek et al., 2011b), decision tree (Marschollek et al., 2011a), support vector machine (Greene et al., 2010a), neural network (Caby et al., 2011), naive Bayesian classfiers (Caby et al., 2011), etc. In this study, the typical classification models with different flexibilities were conducted. Among the models, linear models had relatively low accuracy but advance tree models and support vector machine (SVM) showed excellent accuracy on classifying fallers and non-fallers. In terms of the flexibility of models, linear models had more restrictive assumption, basic tree model had relatively lower flexibility, and advance tree models and SVM had THE highest flexibility. High flexibility of a model is associated with high accuracy of the model (James et al., 2014). The accuracy of models ranged from 0.68 to 0.88, where linear models had lower accuracy and advance model showed high accuracy. Compared with previous study, models with lower flexibility showed the similar accuracy with previous studies. Our linear models including logistic regression and linear discrimination also showed the similar accuracy with the studies of Marschollek et al (2011a) and Liu et al.(2011) at the accuracy around 0.70. The basic decision tree with accuracy of 0.79 also present similar accuracy with the decision tree with accuracy of 0.78-0.80 in the study of Marschollek et al.(2011). The possible reason was that linear models and basic decision tree have restrictive assumptions, so more measures were added to the models but it could not help to improve the model accuracy. On the contrary, advance models with high flexibility showed relatively higher accuracy compared with models in previous studies. Greene et al. (2012) used SVM model to classify fallers and non-fallers based on timed up and go test and the accuracy of the model was evaluated using ten-fold cross validation and showed the accuracy of 71.5%. Our study showed excellent accuracy of 88.5%. This result might be explained by the fact that we included significant measures from different aspects of a balance system, while their studies only used the measures from timed up and go test. Due to the high flexibility of these advance models, more measures from different aspects of a balance system could improve the model accuracy efficiently.

TABLE 4.11: Inertial sensor based fall risk assessment models in previous studies.

Author	Sample size	Task & features	Model	References for the fall	Model validation	Accuracy (%)
Caby et al. (2011)	20 (14 female and 6 male): age 80.85 ± 5.18	25m walk: time, steps, step frequency, spectral entropy, median frequency, etc.	Radial basis function neural network, support vector, k-nearest neighbor, and naive Bayesian classifiers	Clinical assessment	Leave-one-out cross-validation	75–100
Marschollek et al. (2009)	110 (81 female and 29 male) in patients: age 80.	1. Timed up and go test: pelvic sway, step length, number of steps; 2. STRATIFY score; 3. Barthel index.	Decision tree (CART)	Retrospective fall history	Stratified ten-fold cross validation	83–90
Liu et al. (2011)	68 (47 female and 21 male): age 72–91	1. Timed up and go test: total time, step frequency, etc.; 2. sit-to-stand five times test: time, dissimilarity of sit-to-stand cycle, etc.; 3. alternate step test: time, dissimilarity, etc.	Linear regression, linear discriminant classifier	Clinical assessment	Leave-one-out cross-validation	71
Greene et al. (2012)	120 (63 female and 57 male): age 73.7 ± 5.8	Quiet standing: RMS accelerations, angular velocity; median frequency, etc.	Support vector machine	Retrospective fall history	Stratified ten-fold cross validation	71.5
Marschollek et al. (2011b)	50 (37 female and 13 male) in patients: age 81.3	1. Timed up and go test: kinetic energy, pelvic sway, step length, etc. 2. activities of daily life	Logistic regression, decision tree (CART)	Prospective falls	Stratified ten-fold cross validation	65–80
Marschollek et al. (2011a)	50 (37 female and 13 male) in patients: age 81.3	1. Timed up and go test: kinetic energy, pelvic sway, step duration, step length, etc. 2. 20m walk; 3. STRATIFY score; 4. Barthel index	Logistic regression	Prospective falls	Stratified ten-fold cross validation	70–72

4.4.3 Limitations

Some limitations still existed in this study. First, we generated so many measures from different kinds of tests. Then we used significant measures in two-sample t-test, effect size, and ROC analysis as the independent variables to build the models. Some measures might have high correlations between each other, so the independent variables might be redundant for the models. Some methods such as principle component analysis could be used to reorganize the independent variables in the future. Second, we set fall history as the criteria to separate fallers and non-fallers. Fall experience induced many effects on the people such as fear of falling (Legters, 2002). In order to prevent falls in the future, it is reasonable to use the future fall as the criteria for predicting fall risks in the future study. Additionally, in our study, the total weight of the system is 480g, including $30g \times 5$ XSens sensors and 330 g Xbus Master. So the system is not light for the subject. But it may also affect the results. Additionally, in order to make sure all participants walked barefooted comfortably, we considered of keeping the temperature of the room and the floor in all seasons, especially in the winter, the floor was cold for walking, so the participants wore a pair of normal and thin socks to keep warm on the feet. In other seasons, participants just walk barefooted. However, the socks may be a confounding factor, but the effect may be small. Lastly, only old women were recruited in this study to avoid the gender effect on fall risks, the generalizability of the study findings on old men need to be investigated further.

4.5 Conclusion

The purpose of this study was to develop the models for classifying fallers and non-fallers. We conducted an experiment of 195 participants using our designed protocol, which included seven main tests: sensory integration test, limits of stability test, sit-to-stand five times test, timed up and go test, reaction test, and short falls efficacy scale international questionnaire. In the statistical analysis, many inertial sensor based measures derived from test showed significant differences between fallers and non-fallers using two-sample t-test and significant discrimination ability on separating fallers and non-fallers using ROC curve analysis. Faller showed worse visual and vestibule systems, weaker muscular strength, decreased flexibility of the knee joint, and slower information processing speed than non-fallers. Fallers also had more difficulties on performing postural stability, functional reach, sit-to-stand five time tests and timed up and go test compared with non-fallers. According to the model flexibility, six representative models were used to classify fallers and non-faller, including logistic regression, linear discriminant analysis, classification and regression tree, boosted tree, random forest, and support vector machine radial basis function (SVMRBF). 10-folder cross-validation was used to evaluate the model performance. Restrictive models of logistic regression and linear discriminant analysis presented relatively lower accuracy around 0.70 on fall classification but they had good interpretability. High flexible models of SVMRBF, boosted tree and random forest showed excellent accuracy (>0.85) on fall classification but they had poor interpretability. Due to the trade-off between the model interpretability and flexibility, lower flexibility models had good interpretability but low accuracy and high flexibility models had high accuracy but poor interpretability. Therefore, depending on the research purpose, the model with proper flexibility could be selected for fall classification among available models in this study.

Chapter 5

Development of methods for identifying the underlying causes of high fall risks in older people

5.1 Objective

In Chapter 4, we used six statistical models for fall classification. If a senior was classified as a faller or at a high risk of falling by our models, it was important to identify the causes of high fall risk for fall prevention. In this Chapter, the aim was to identify the underlying causes of high fall risks in the individuals. Significant measures identified from the previous chapter were further analyzed and two methods were integrated for fall evaluations: the classification and regression tree (CART) model and the profile assessment. The CART model identified the possible causes of high fall risks based on the tree-based relationships between fall related factors and fall category (faller or non-faller). The profile assessment examined abnormal fall related factors using the normal distributions of significant and representative measures.

5.2 Method

In Chapter 4, six typical statistical models with different flexibilities for classifying fallers and non-fallers were proposed. Generally, there is the trade-off between the model predictive accuracy and model interpretability (James et al., 2014). Advanced models including boosted tree, random forest and SVMRBF showed excellent model accuracy on fall classification. However, these models worked more like a 'black box', which absorbs the features or independent variables, trains the data and later outputs the results. It was difficult to interpret how the model generated results from available independent variables. As a result, it was impossible to use these advanced models to identify the causes of high fall risks. In terms of logistic regression and linear discriminant analysis, the relationships between independent variables and response variables were easily interpretable, but were also unable to identify the factors of high fall risks.

On the other hand, decision tree involves stratifying or segmenting the predictor space into a number of simple regions recursively, e.g. classification and regression tree (CART). This prosperity built tree-based relationships between risk factors and fall. Because of this, the basic tree-based models, such as CART (Delbaere et al., 2010), logistic regression tree (Yamashita et al., 2012), and tree-structured survival analysis (Stel et al., 2003a), have been used for identifying high fall risk factors in several studies. However, the decision tree algorithms were not very robust (Last et al., 2002). Small variations in the training data could result in different trees. For example, changing variables, excluding duplicated information, or altering the sequence midway could lead to major changes and possibly require redrawing the tree.

Meanwhile, Lord et al. (2003b) proposed the profile assessment method to identify the causes of high fall risks. The profile assessment method evaluated the performance of important fall related factors based on the normal distribution of a large-scale sample. It could provide much detailed information on each individual measure/factor relative to the normative data. Different from the decision tree method, the structure of the profile assessment method was stable and was not affected by small variances of the training data. However, since the fall information was not used directly in the profile assessment method, the relationships between risk factors and fall category were weak.

TABLE 5.1: Comparisons of two methods for identifying the causes of high fall risks

Methods	Description	Advantages	Disadvantages
Decision tree (Delbaere et al., 2010)	To identify the causes of high fall risks based on a tree-based relationships between risk factors and falls. E.g. classification and regression tree (CART).	Clear relationships between risk factors and falls, and interactions among factors.	Decision tree structure is unstable (Last et al., 2002), sensitive to the change of training data, e.g. variables or sample size.
Profile assessment method (Lord et al., 2003b)	To identify abnormal factors based on normal distribution of the factor measures as the causes of high fall risks.	Stable profile structure and reference range.	Weak relationships between risk factors and falls, and interactions among factors

Therefore, the decision tree built clear tree-based relationships between risk factors and falls, but was sensitive to fall and thus unstable. On the other hand, the profile assessment had stable structure but weak relationships between risk factors and falls. Thus the two methods are complementary to each other. Therefore, we developed the CART-PA method to integrate the CART model and profile assessment method for identifying the causes of high fall risks. As shown in Figure 5.1, to identify the causes of risks, CART model and profile assessment methods are utilized to find the causes. Then a factor identified by two methods is considered as the main factor, otherwise the factor is considered as the possible factor. Comparing with using CART model or profile assessment method only, CART-PA method could generate reinforced causes of high risks. The results can include the main factors and also possible factors.

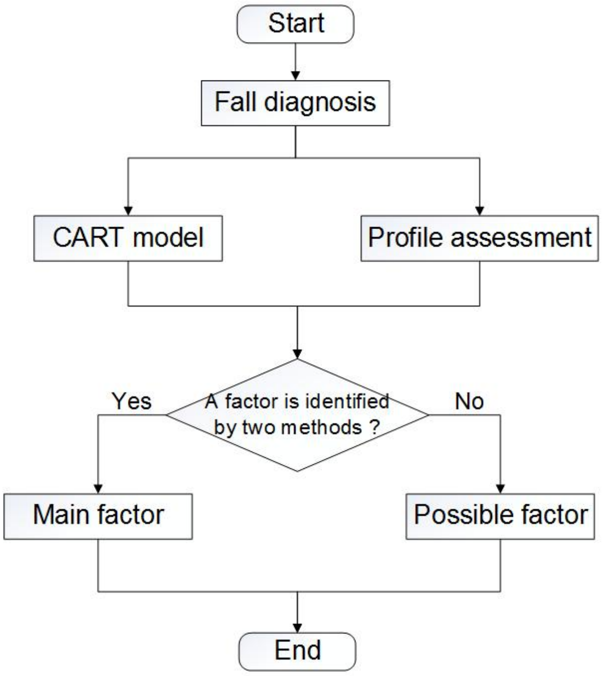


FIGURE 5.1: The algorithm of the CART-PA method.

According to the CART model, the decision tree was generated from the significant measures in the tests. Figure 5.2 shows the algorithm to generate a decision tree based on the CART model. The algorithm starts with the whole population and sequentially divides it into subgroups by independent variables. Then the best split variable is selected first and provides the first partition by the cutoff value. Both split variable and cutoff values were determined by Gini impurity. After this, the remaining variables are examined to determine whether they can provide further discrimination, and this process continues until the sample size is smaller than five or no significant change on Gini impurity.

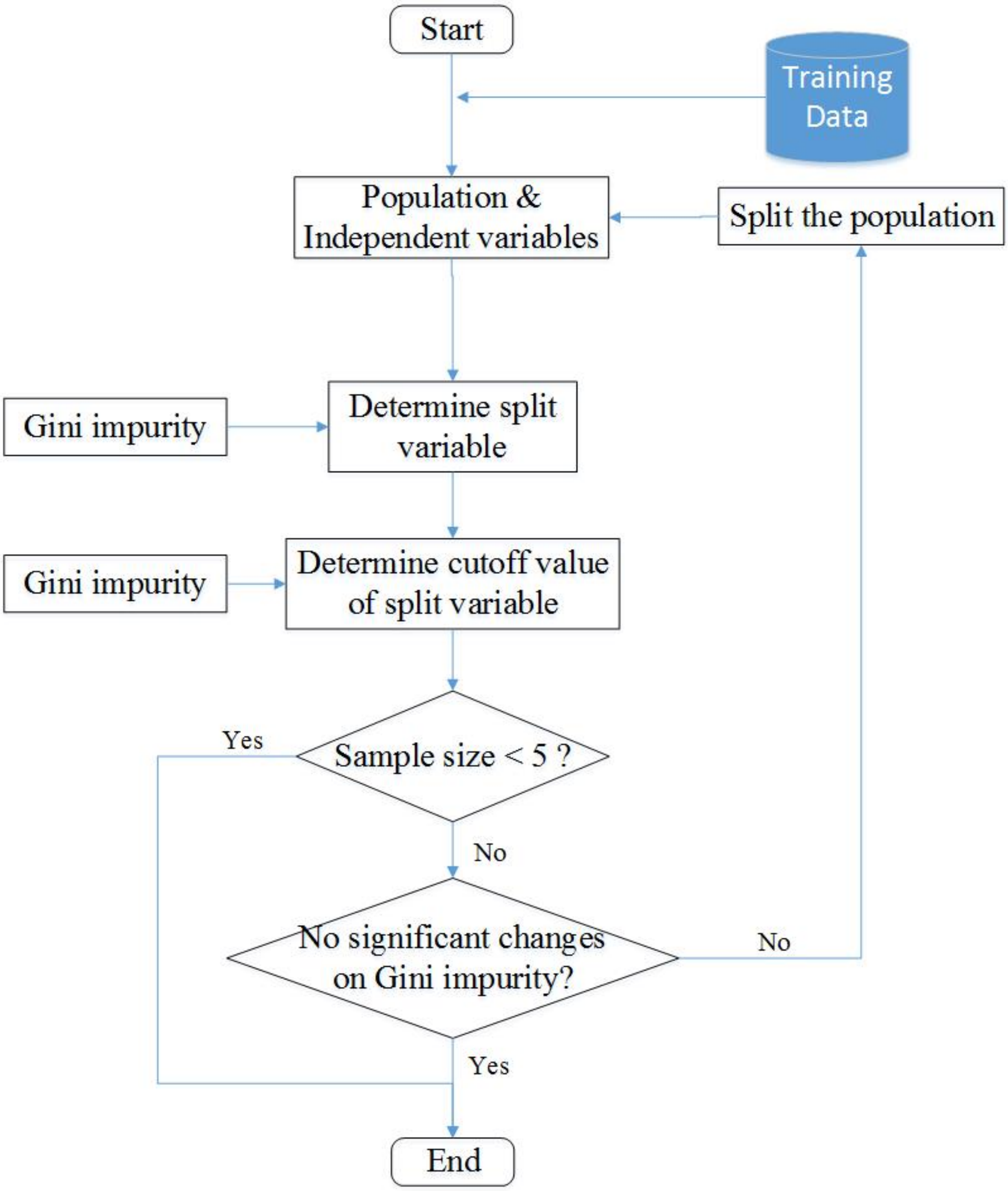


FIGURE 5.2: The algorithm of the CART model to construct the decision tree.

In our study, first all participants were separated into two groups based on the short FES-I score at the cutoff point of 10 using the Gini impurity. Subsequently, participants in the short FES-I group with cutoff below than 10 were split into two groups based on the jerk in sit-to-stand five times test. The group was split recursively until all terminal nodes became non-significant pure or the number of participants in the nodes were less than 5. Finally, the tree was constructed, as shown in the figure 5.5. The normal tree node was represented by the rectangles while the terminal tree node was represented by the ellipses. The normal tree node contains the test, the measure and the cutoff point. In addition to the information on the normal tree node, the terminal node also included the total number of participants and the percentage of fallers within the participants.

In our study, many measures could assess one profile (or a factor). For example, the visual system was assessed by eleven measures (seeing Table 4.3). Because of it, it was necessary to choose the most useful measures to reflect the profiles. Therefore, if there were more than two significant measures for evaluating a profile, the first two significant measures that had the highest area under the ROC curve (AUC) would be selected to represent this profile, because AUC measured the discriminate power of the measure to classify fallers and non-fallers. Figure 5.3 presents 15 measures based on the profiles of a participant, including the visual system, vestibular system, central nervous system, motor function, postural stability, postural response, stability limits and gait stability. Each profile was assessed by the measures derived from the tests in the protocol. For example, the visual system could be measured by RMS jerk of angular velocity in AP direction and RMS equilibrium score in ML direction.

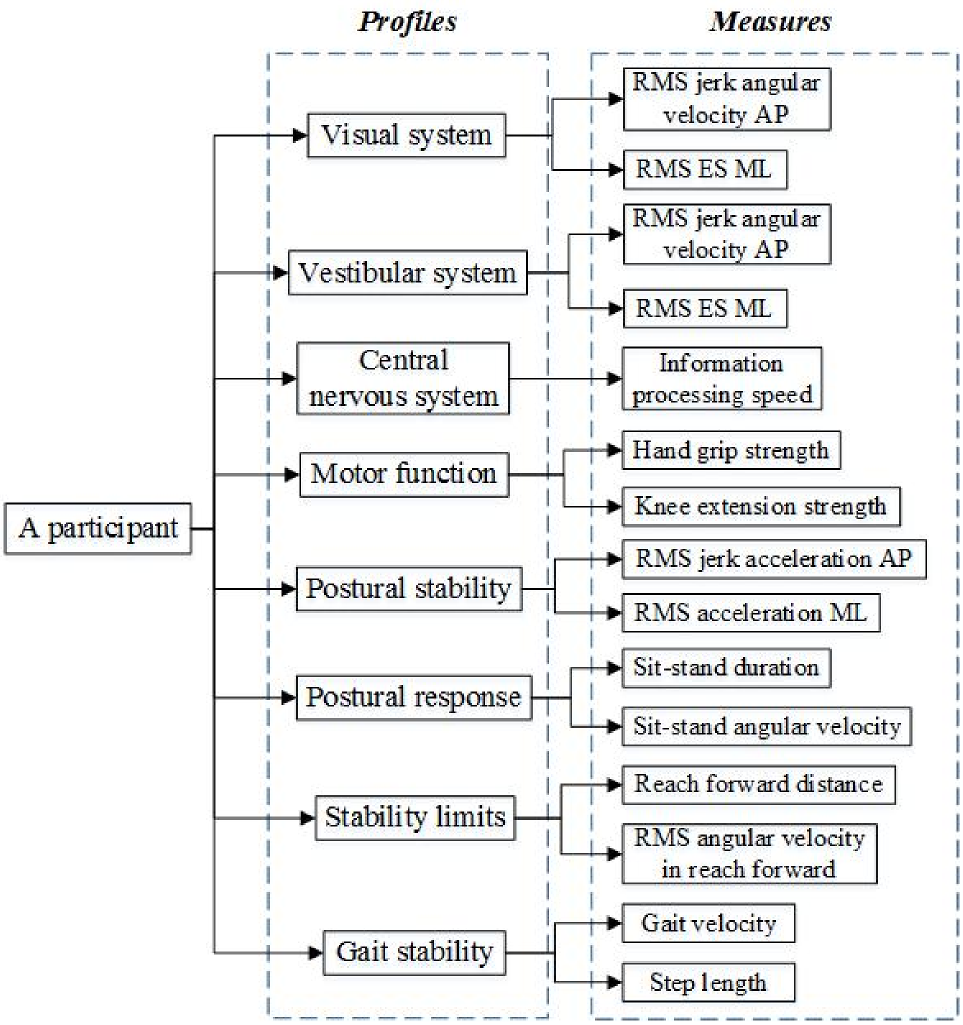


FIGURE 5.3: Components and representative measures of a participant profile. AP: anteroposterior; ML: mediolateral; RMS: root mean square; ES: equilibrium score.

In this method, first 95% of the normal distribution of the population was used as the reference to generate the normal range with lower and upper limits from the large-scale sample. When a high value represented poor performance, the measure value larger than the upper limit was defined as an abnormal range. When low measure value represents the poor performance, then the measure value smaller than the lower limit was identified as an abnormal range. Once a subject's test performance results were calculated, these results could be compared to the reference value to determine whether the related measures were abnormal. Additionally, the test results could also be converted to z score to compare across different measures, with the z scores being calculated using the mean and standard deviation of measures (Table 5.2) by below equation:

$$z = \frac{sign \times (measure\ value - mean)}{standard\ deviation} \tag{5.1}$$

Sign is +1 if higher measure value indicates better performance; otherwise, -1 will be assigned. Hence, all measures could be compared in the common standard for easy visualization and fall risk evaluation. The abnormal range was z score lower than -1.96. Finally, a profile graph that includes all profiles could be plotted from z scores of all profiles.

TABLE 5.2: Mean, standard deviation and normal range based on 95 percentile of the profile measures.

Profiles	***Measures***	***Mean***	***Standard deviation***	***Abnormal range***
Visual system	RMS jerk angular velocity AP	2.32	0.87	> 4.46
	ES ML	0.89	0.045	< 0.80
Vestibular system	RMS jerk angular velocity AP	4.17	2.24	> 9.72
	ES ML	0.82	0.077	< 0.66
Central nervous system	Information processing speed	6.35	1.80	< 3.68
Fear of falling	Short FES-I	11.80	4.21	> 21
Motor function	Hand grip	0.35	0.071	< 0.20
	Knee extension	0.25	0.080	< 0.10
Postural stability	RMS jerk acceleration AP	13.00	7.07	> 29.67
	RMS acceleration ML	0.0071	0.0020	> 0.012
Postural response	Sit-stand duration	1.01	0.22	> 1.49
	Sit-stand angular jerk	1525.40	607.04	< 578.40
Stability limits	Reach forward distance	24.85	7.27	< 12.04
	RMS angular velocity in reach forward	0.24	0.094	< 0.078
Gait stability	Gait velocity	0.74	0.12	< 0.50
	Step length	0.38	0.045	< 0.30

Figure 5.4 shows a typical example of the distribution and z score of information processing speed. First, using 95% as the reference, the range of information processing speed was between 3.68 and 9.04. Since a low information processing speed represents poor performance, the abnormal range is information processing speed smaller than 3.68. A subject had the information processing speed of 3.25, which is lower than 3.68. The z score of information processing speed was also calculated and presented in the figure. We could conclude that the subject had a much lower information processing speed than the average of information processing speed based on a large-scale sample. So the subject may have an impaired central nervous system that was measured by the information processing speed. To generate the z score, we could derive the mean and standard deviation from large-scale information processing speed data (in the example, $mean = 6.35$ and $standarddeviation = 1.20$). By using this mean and standard deviation, the subject's information process speed of 3.25 would be standardized to z score of -2.27.

Finally, CART model and the profile assessment were combined to identify the underlying causes of high fall risks. If one factor was identified as the cause by two methods, then that factor would be considered as one of the causes of high fall risks. If one factor was identified as the cause by only one method (either the CART model or the profile assessment), then the factor was the potential cause of high fall risks.

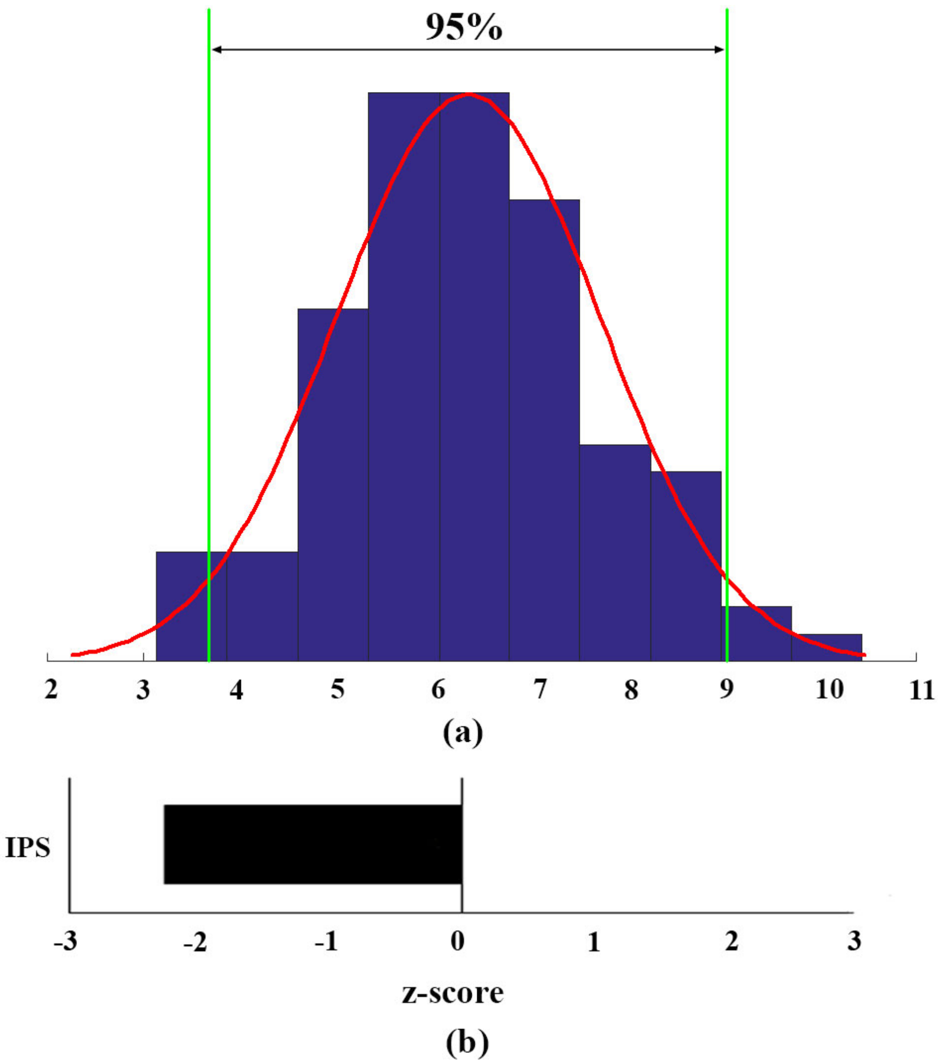


FIGURE 5.4: A typical example of the distribution and z score of information processing speed. (a) The plot of normal distribution probability density function (PDF) and histogram based on the information processing speed data (mean=6.35 and standard deviation=1.20. Using 95% as the reference of normal performance, the lower limit is 3.68 and the upper limit is 9.04.). (b) a subject's information processing speed of 3.25 was standardized to z-score of -2.27 (Using 95% as the reference, lower limit of z-score is -1.96, upper limit is 1.96). IPS: information processing speed.

5.3 Results

Once the tree was built, we could utilize it to predict the fall risk and identify the underlying causes of high fall risks. First, a new subject has to complete all tests in our test protocol. Then fall related measures would be calculated based on the tests. Finally, the subject would fall into one of the end nodes in the tree. The tree end node showed a fall probability of the subject directly. We can trace back the path based on measures of the subject in the tree model to identify the possible reason of high fall risks. For example, there are two participants who were named as participant 1 and participant 2 in the experiment. In the Figure 5.5, if participant 1 falls into the green tree end node following the green path, the subject has very low fall risk (3%). From the green path, we can conclude that the participant has a low fear of falling, good sit-to-stand ability, good sensory system and good vestibular system. If participant 2 falls into the red end node following the red path, the subject has very high fall risk (90%). From the red path, we also can conclude that this participant has a relatively high fear of falling, poor central nervous system ability, but the good functional reach ability from limits of stability test. So the possible causes of high fall risk are fear of falling and poor central nervous system ability.

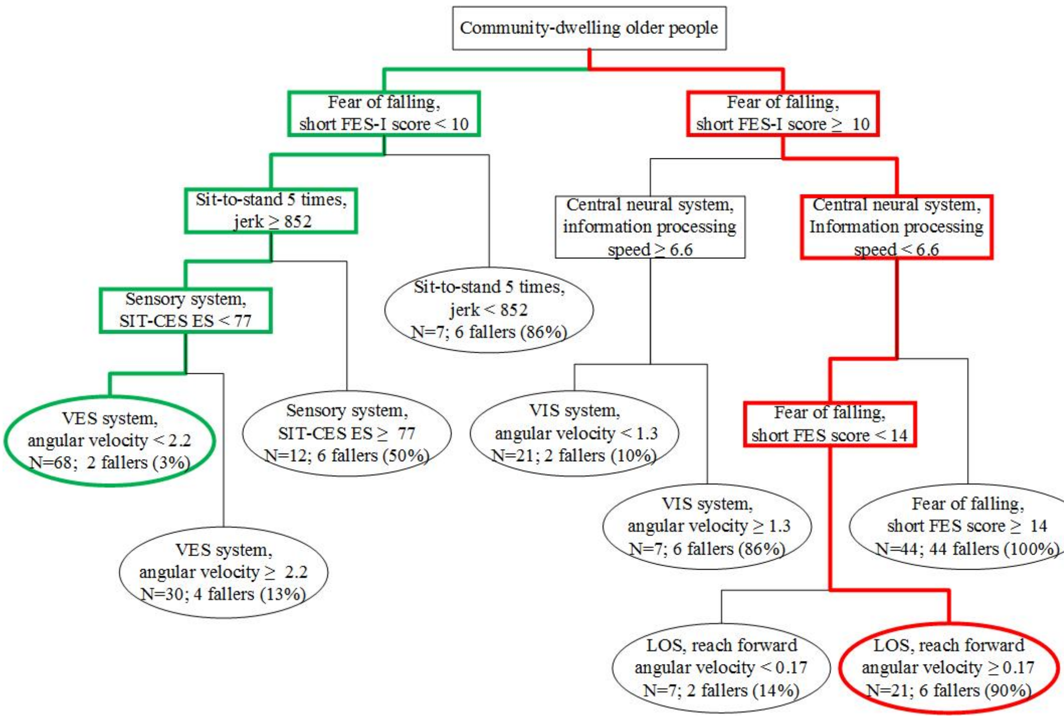


FIGURE 5.5: Classification and regression tree for fall risk assessment. In the tree, rectangles represent tree nodes and ellipses represent tree end nodes. Normal tree nodes include the factors and the measures of the factors. The end nodes include factors, measures, total number of the group and the number of fallers (fall probability). FES-I: falls efficacy scale international; LOS: limits of stability; SIT-CES ES: equilibrium score of composite equilibrium score measures in sensory integration test; VES: vestibular. VIS: vision.

Using the same participants in the decision tree, Figure 5.6 showed the profile graph of participant 1 based on z scores of representative measures. From the figure, it was clear to observe overall performance of the participant. Participant 1 showed good performance on all profiles. Figure 5.7 presented the profile graph of participant 2 based on z scores and z score of information processing speed was smaller than -1.96. Therefore, information processing speed could be the cause of participant 2.

Therefore, combining the results from the CART model and the profile assessment, participant 1 was healthy with very low fall risk. Participant 2 was at high fall risk, and the cause of high fall risk was poor central nervous system and the potential cause of high fall risk was the fear of falling.

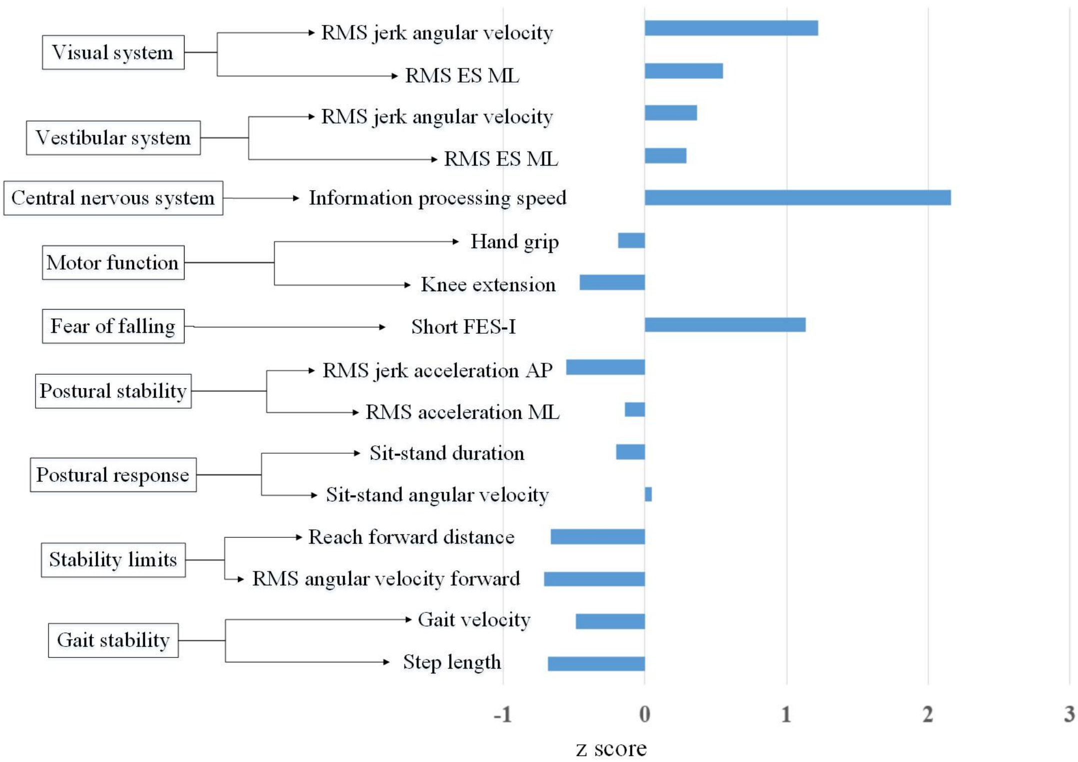


FIGURE 5.6: The profile graph of participant 1.

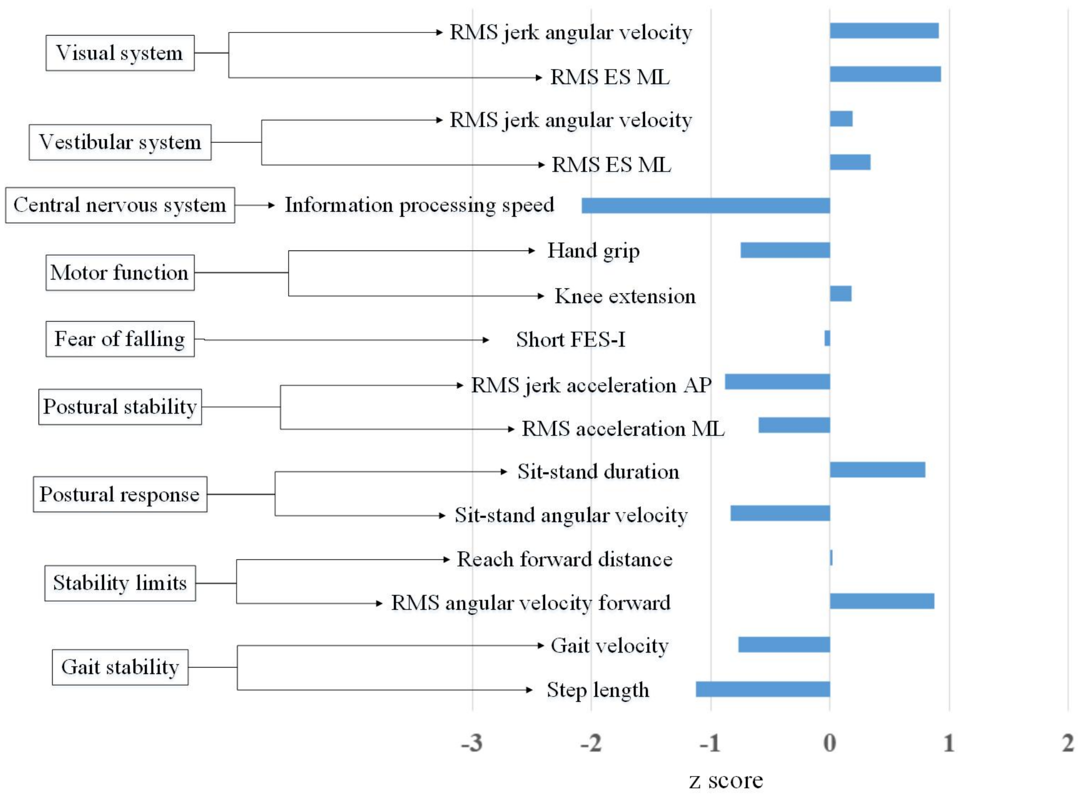


FIGURE 5.7: The profile graph of participant 2.

5.4 Discussion

In the decision tree using CART model, fall related factors were that the fear of falling measured by short FES-I score, information processing speed of central nervous system, sit-to-stand five times jerk, and sensory system including visual and vestibular systems, functional reach angular velocity. In previous studies, many similar tree models were also proposed to assess fall risks. For example, CART model was also used in the study done by Delbaere et al (2010), in which the factors were actual fall risk measured by the score of physiological profile assessment (PPA), level of disability, exercise, executive functioning, and coordinated stability. In addition to CART model, Stel et al. (2003b) proposed the tree-structured survival analysis (TSSA). They considered functional limitations, performance tests, grip strength, alcohol, pain, education, dizziness as the factors. Yamashita et al. (2012) utilized the logistic regression tree analysis to create the decision trees, which included factors of age, activities of daily living (ADL) limitations, and instrumental activities of daily living (IDAL) limitations. Comparing the factors in our study with previous studies, factors in our study were associated with special functions of balance system (E.g. visual system), but factors in previous studies were associated with composite performance such as disability, ADL limitations. If the causes of high fall risk were composite performance, the exact reasons of high fall risks would still be unknown. Moreover, fall risk factors used in our study were also modifiable. However, in previous studies, many factors used were unmodifiable such as age (Yamashita et al., 2012), education (Stel et al., 2003b). If unmodifiable factors were the causes of high fall risk, it would be useless on fall prevention even if they were identified as the causes. Considering the fall related factors used in our study, our CART model was more advanced than models in previous studies on identifying the causes of high risks of falling for preventing falls.

In the profile assessment method, fall related factors covered physiological, psychological, and integrated functions. Physiological function (Winter, 1995) was related to the sensory system including somatosensory, visual, and vestibular systems, central nervous system of cognitive function, and motor function. Psychological function contained the fear of falling. Integrated function (Horak et al., 2009) was associated with biomechanical constraints, sensory orientation, stability limits, anticipatory postural response, and stability in gait. However, the study that was done by Lord et al. (2003b) only used the physiological factors which contained vision, vestibular function, peripheral sensation, reaction time and muscle force. They also acknowledged the omission of other important factors in their approach as one of the limitations of their study. Compared with previous study, our profile assessment method could identify more possible causes of high risks of falling. Therefore, our combined method that combines the CART model and the profile assessment method could have a higher probability on identifying the factors resulting in high risks of falling than previous studies. Also since these factors were modifiable, the results could be useful on fall prevention.

In the decision tree, for the classification and regression tree model, the splitting variables and the cutoff values in the tree were determined by the Gini impurity. However, the Gini impurity was sensitive to changing variables and sample size (Last et al., 2002). The decision tree could be affected significantly due to the changes of training sample population. Additionally, we found that short FES-I score that measures the fear of falling, information processing speed of central nervous system, sit-to-stand five times jerk, and sensory system including visual and vestibular systems, functional reach angular velocity were most important measures on classifying fallers and non-fallers among all significant measures in the tests (around 40 measures). Falls efficacy scale measures how much do old people concerns of falls while performing special activities (Tinetti et al., 1990). It is the integrated self-evaluations of their abilities that were associated with falls systematically. Due to the fear of falling, people will also limit their physiological activity (Legters, 2002), which enhances to increase the fall risk. central nervous system also played a core role on balance control, for receives the stimuli from a sensory system, makes the decision and sends the control stimuli to motor control system for achieving balance or avoiding falls (Horak, 2006). Visual and vestibular systems were also found to be important factors of falls (Ambrose et al., 2013). Our findings also showed that sit-to-stand five times test and functional reach may be the efficient tests for classifying fallers and non-fallers.

Some limitations still existed in this study. First, the decision tree separated population into subgroups recursively by the independent variables. Some terminal tree node could have small sample sizes. The fall risk of each end tree node was based on the percentage of fallers. If the sample size is too small in the tree end node, the fall probability is not stable and affected by few data significantly. We are still conducting additional experiment to increase the sample size for generating stable results. The other was that we used two methods to identify the underlying causes of high fall risks. We intend to combine results from two methods to analyze the real causes. However, in the current stage, we didn't propose the methods to validate our results. One standard reference could be the evaluation results from the doctors in the hospital.

5.5 Conclusion

In this study, we proposed CART-PA method to identify the underlying causes of high fall risks. Since many factors from different aspects were considered, the possible causes of high fall risks could be identified effectively. Additionally, fall evaluation results could be helpful for fall prevention, because these factors were measurable and modifiable. Additionally, CART-PA method was integrated by the CART model and profile assessment method. The CART model built a tree based relationship between fall related factors and fall and interactions among factors, which was effective on identifying the causes of high fall risks. But the tree structure was unstable could be affected by small variance. On the other hand, the profile assessment was developed based on the normal distribution of fall related factors. So it was useful on identifying abnormal factors but may ignore sensitive risk factors. Therefore, CART-PA method could generate reinforce results of the factors of high fall risks.

Chapter 6

Development of an inertial sensor based fall risk assessment system

6.1 Objective

The purpose of this study was to develop an inertial sensor based prototype system for fall risk assessment. The system was designed to realize our proposed fall risk assessment methods, which included the hardware and software. The hardware consisted of five low-cost individual wireless inertial sensors and a wireless transmission device; it was developed to collect the data simultaneously. Computer-based software was developed to process the raw data obtained from the sensors, calculate the measures for each test in the protocol, and build fall risk assessment models.

6.2 Overview of fall risk assessment system

Figure 6.1 presents the overview of the developed fall risk assessment system, which mainly includes the hardware for data acquisition and the software for fall classification and evaluation. The data acquisition hardware contains five wireless inertial sensors and one Bluetooth USB adapter for wireless transmission device. These five sensors were attached to the pelvis and the upper and lower parts of both legs. Data from the sensors were then transferred to a personal computer (PC) through the wireless transmission device. A multi-sensor management software (Shimmer Inc.) in a PC or laptop was used for sensor communication and data collections. Then we developed graphical user interface (GUI)-based software to process the raw data from sensors, calculate measures based on raw data in different tests, and build fall risk assessment models for fall classification and evaluation.

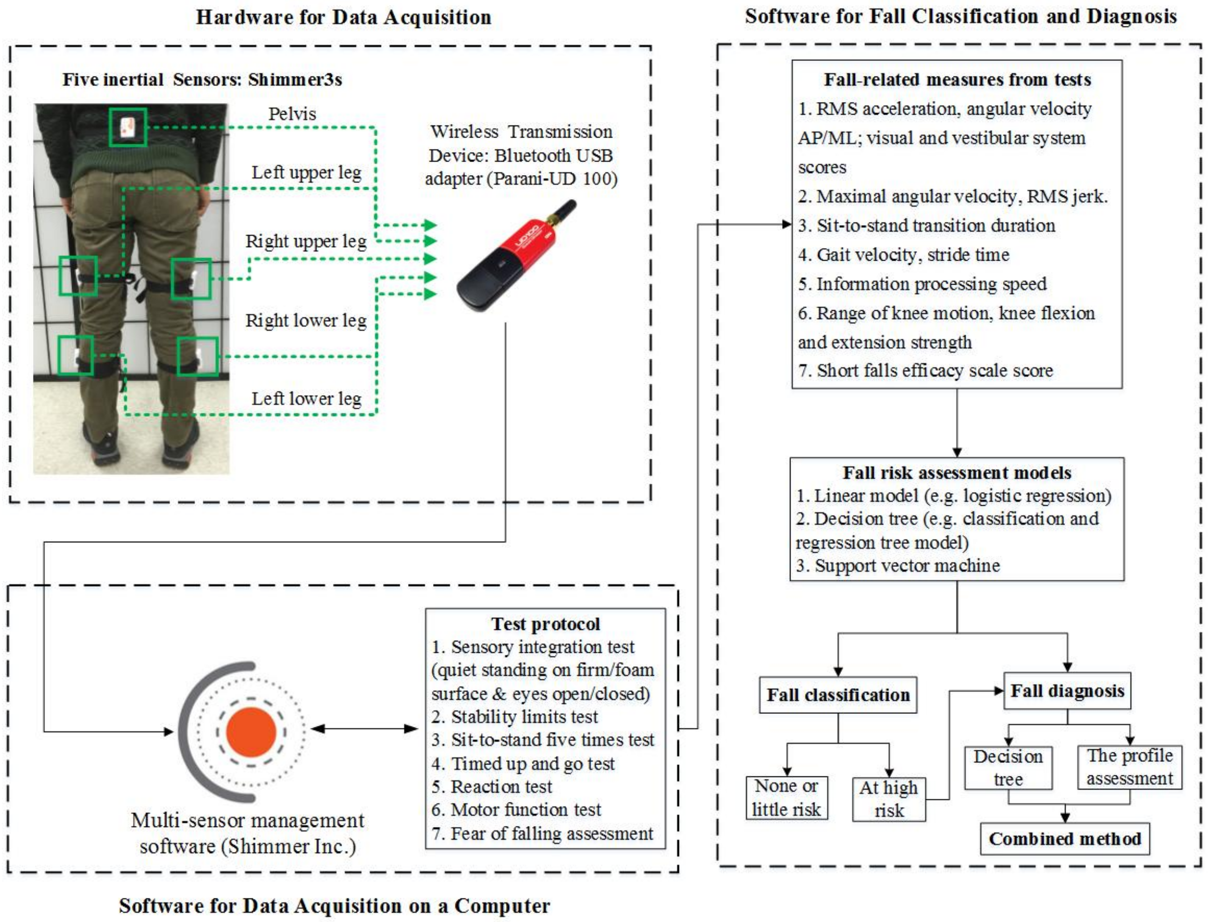


FIGURE 6.1: Overview of an inertial sensor based fall risk assessment.

6.3 Hardware development

Our study utilized inertial sensors to acquire data while participants were performing different tests. The requirements for the sensors were: (1) five wireless inertial sensors with a combination of accelerometer, gyroscope, and magnetometer; (2) synchronized live data streaming and collection through five sensors;

(3) the sensors' outputs of 3D accelerations, 3D angular rate, and 3D magnetic field intensity at a frequency of 100 Hz; and (4) a low price. We searched for available inertial sensors on the Internet, and a list of available sensors is presented in Table 6.1.

TABLE 6.1: Available products of inertial sensors.

Product	***Sensor***	***Wireless***	***Sync***	***Price per sensor ($)***
Isen SIT-IBS	accelerometer, gyroscope, and magnetometer (100Hz)	Yes	Yes	865
LightBlue Bean	acceleraometer (30Hz)	Yes	No	30
Shimmer3	accelerometer, gyroscope, and magnetometer (100Hz)	Yes	Yes	380
Opal I2M	accelerometer, gyroscope, and magnetometer (100Hz)	Yes	Yes	>3000
ProMove mini	accelerometer, gyroscope, and magnetometer (100Hz)	Yes	Yes	469
Sensoplex SP-10C	accelerometer, gyroscope, and magnetometer (100Hz)	Yes	No	100
VectorNav VN-100	accelerometer, gyroscope, and magnetometer (100Hz)	No	No	800
Xsens MTi-100	accelerometer, gyroscope, and magnetometer (100Hz)	Yes	Yes	>3000
x-BIMU Kit	accelerometer, gyroscope, and magnetometer (100Hz)	Yes	No	300

Among the available sensors, Isen SIT-IBS, Shimmer3, Opal I2M, ProMove mini, and Xsens MTi-100 were acceptable, in terms of the wireless and sync functions. Among these sensors, Shimmer3 appeared to be the cheapest sensors that could satisfy all of our requirements. Therefore, we purchased the Shimmer3s as our inertial sensors from Shimmer Inc., which cost approximately $380 per sensor. The

Shimmer3 (Figure 6.2) is a wireless sensor planform that contains a TI MSP430 microcontroller, Bluetooth radio support, a MicroSD slot supporting up to 2 GB of flash storage, and a 450 mAh Li-polymer rechargeable battery (Burns et al., 2010). The Shimmer incorporates tri-axial MEMS accelerometer, gyroscope, and magnetometer; it measures $51 \times 34 \times 14mm$ and weights 23.6 g.

To communicate with the computer, Shimmer3 contains an embedded Bluetooth module that can be connected to a computer with a built-in Bluetooth module. However, many of the available desktop computers are not equipped with a Bluetooth module. In addition, such Bluetooth modules equipped in computers is class 2 type Bluetooth, which have a small range of 10 meters and weak signal strength. Hence, we added a Parani-UD 100 (Sena Technologies Inc.) as the wireless transmitter. The Parani-UD 100 is a class 1 type Bluetooth USB adapter that supports 300 meters of wireless transmission distance by default. Due to its greater communication distance compared with other regular Bluetooth USB adapters, it is widely used for industrial or special applications. Therefore, the Parani-UD 100 was utilized for sensor communications and signal control between the computer and sensors.

(a) (b) (c)

FIGURE 6.2: System hardware: (a) Shimmer platform; (b) Shimmer base for multiple sensor synchronization; (c) Bluetooth USB adapter for data transmission between inertial sensors and the computer.

6.4 Software development

6.4.1 Development platform

The software was designed to process the data acquired from the hardware, calculate measures based on the tests, and perform fall classification and evaluation. Tasks in the software were designed mainly for data analysis purpose. In Windows 7, C sharp, developed by Microsoft Inc., is commonly used to develop GUI software. Matlab, developed by MathWork Inc., is another high-level language with an interactive environment that provides various toolboxes for algorithm development, data visualization, data analysis, numeric computing, and GUI design. Compared with C sharp, Matlab is more professional and powerful in processing of raw sensor data, calculating measures, and constructing the statistical models. Therefore, the GUI was developed using Matlab R20015b on the operation system of Window 7 64bit operation system (Microsoft Inc.).

6.4.2 GUI design

Figure 6.3 shows the overall interface of the fall assessment system. Our software consists of three main modules: data import, measure calculation, and fall assessment. The data import module contains the following functions: opening data files, resampling data, and visualizing and exporting data. The measure calculation module includes the calculation of sensory integration test measures, limits of stability test measures, magnitude and gait measures in timed up and go (TUG) test , joint angles measures in the TUG test, turning measures in the TUG test, flexibility measures in the motor function test, and input measures. The fall assessment module involves the functions of fall classification and evaluation.

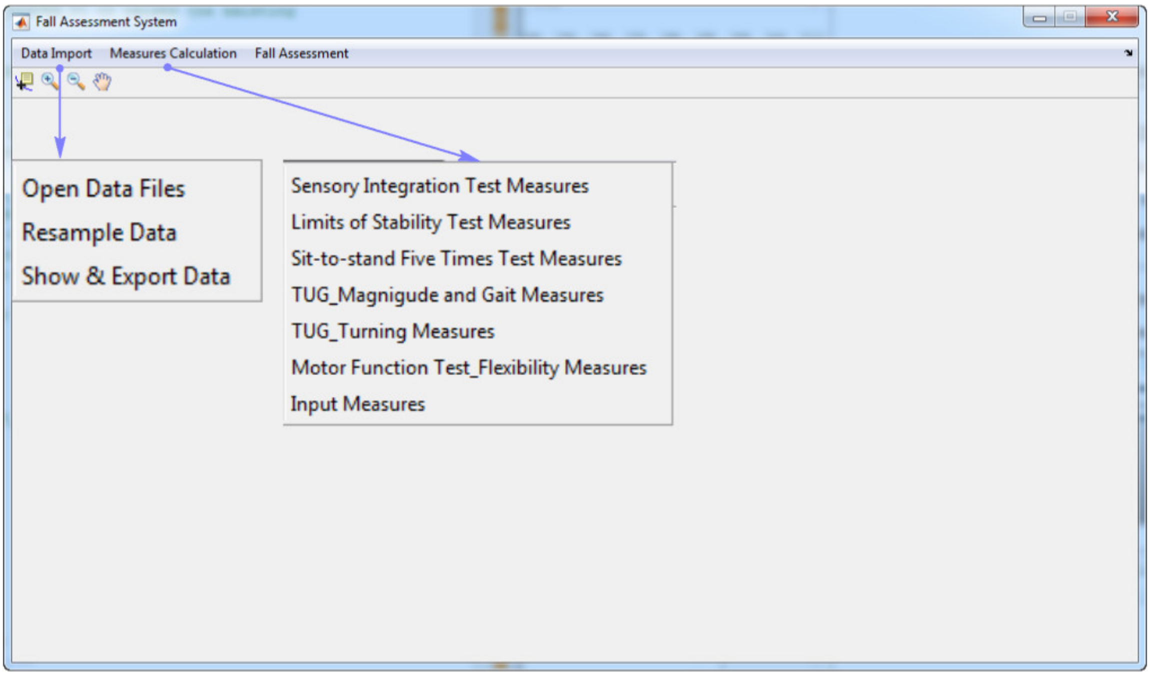


FIGURE 6.3: Fall assessment system overall interface.

6.4.3 Operations and main functions of the software

The data collected by the hardware were initially imported into the software. Measures in the different tests were then calculated based on the data. Finally, these measures were used in the models to identify individuals at high fall risk and then identify the possible causes.

The data import module was designed to input the data file of five inertial sensors, resample the data from the five sensors for time synchronization, and visualize and export the resampled data. The raw data from the hardware were 3D accelerations, 3D angular rates, 3D magnetization and 4D orientation represented by the quaternion. The open file function was used to combine all sensor data files as a unit and store the data in the database. Raw sensor data were recorded based on the same reference time (PC time), but there were some small shifts on time serials between different sensors. In addition, the sample rate appeared to be close to the number that we could set during data acquisition, but was not exactly the number that we expected. Consequently, the data resample function was utilized to identify the start and end points of all sensor time serials and then resample all data to the same frequency (100Hz).

After the data were imported and resampled, the resampled data could be plotted and exported in the software (Figure 6.4). First, users had to load the file that they wanted to check or export by clicking the 'Load data file' button. After selecting the files, the file names were shown in the interface. Then users needed to select the sensors and data type of the data. Once the sensors and data type were checked, the selected data were automatically plotted in a figure. If users intended to export the data file, they could simply click the "export" button and choose the path or folder in which they wanted to store the data, which was saved in the CSV format.

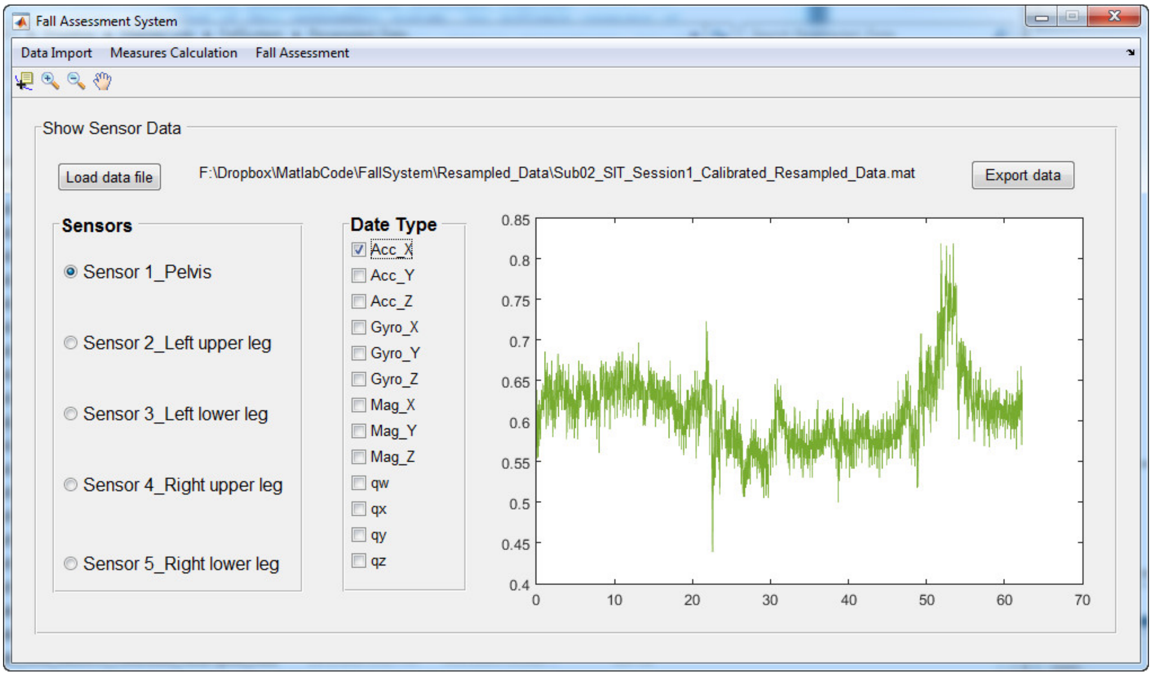


FIGURE 6.4: The interface of data visualization and export function.

After importing the data, the measure calculation module was designed to calculate inertial sensor based measures and input other necessary measures acquired from other methods, such as functional reach distance and muscular strength. According to measures in the tests, six sub-modules were used for calculating measures: sensory integration test measures, limits of stability test measures, sit-to-stand five times test measures, magnitude and gait measures of the TUG test, turning measures of the TUG test, and flexibility measures of motor function test. Figures 6.5 and 6.6 present the operations to calculate measures. In general, three steps were used to calculate measures: loading the data, identifying the feature points (E.g. the start and end points of functional reach), and calculating the data. For example, in the limits of the stability test measures (Figure 6.5b), first the data were loaded and the file names were shown in the textboxes. The checkboxes located beside the textboxes were checked to plot the pelvis orientation and the start and end points of the functional reach. This procedure was done to examine whether the automatically determined start and end points of the functional reach were correct or not. In the figure, the start and end points were generated by our algorithms. If the points were not correct, users could point to the figure, find the correct one, note the start and end points in the textboxes, and click the "Update" button to update the start and end points. Later, the start and end points would be renewed in the figures. After the start and end points were identified, users could click the calculate measures button and the results were presented in the data table.

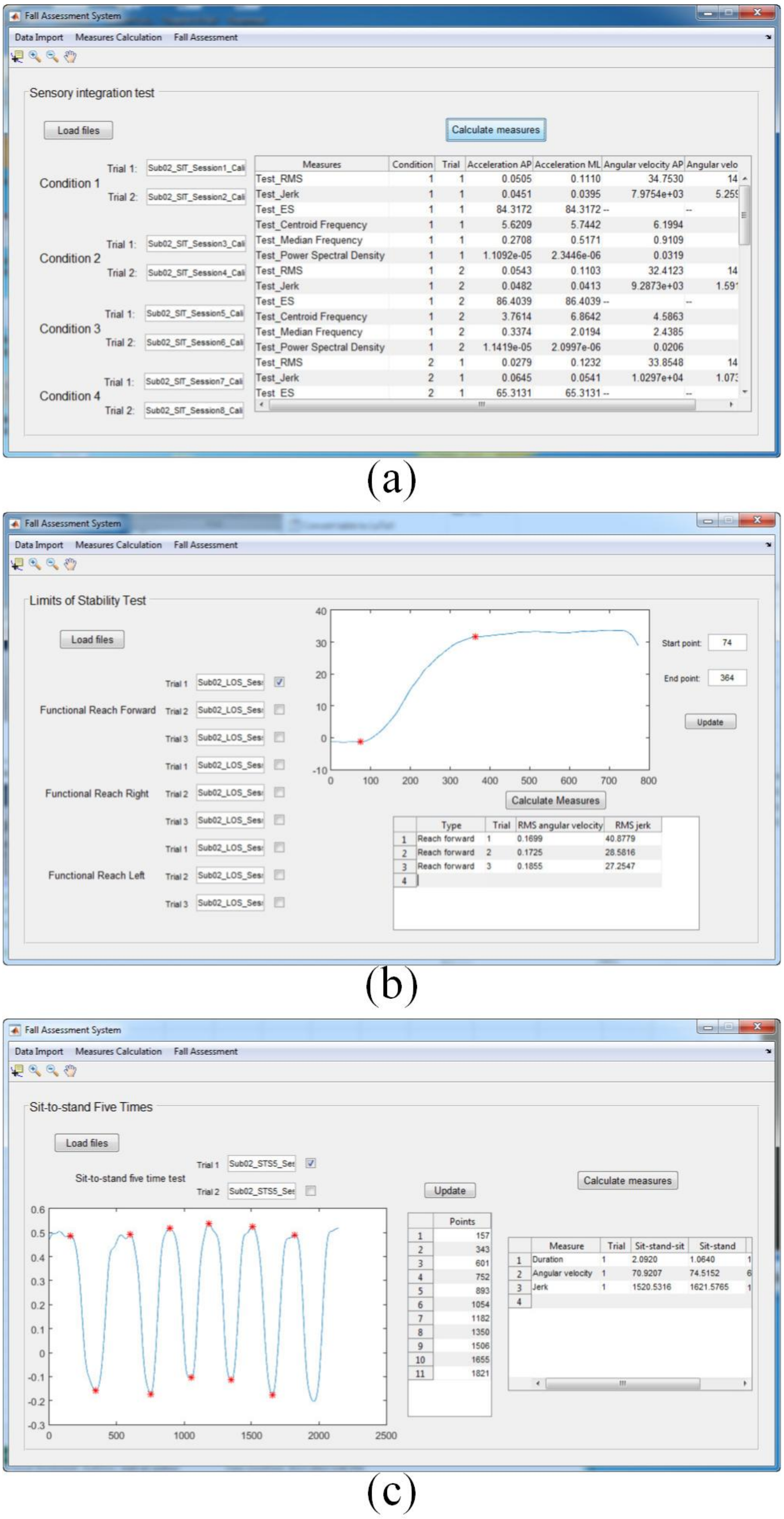
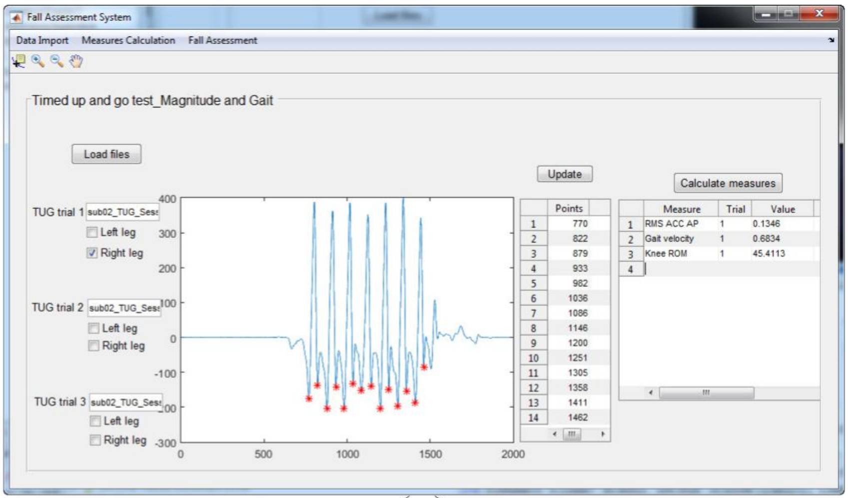
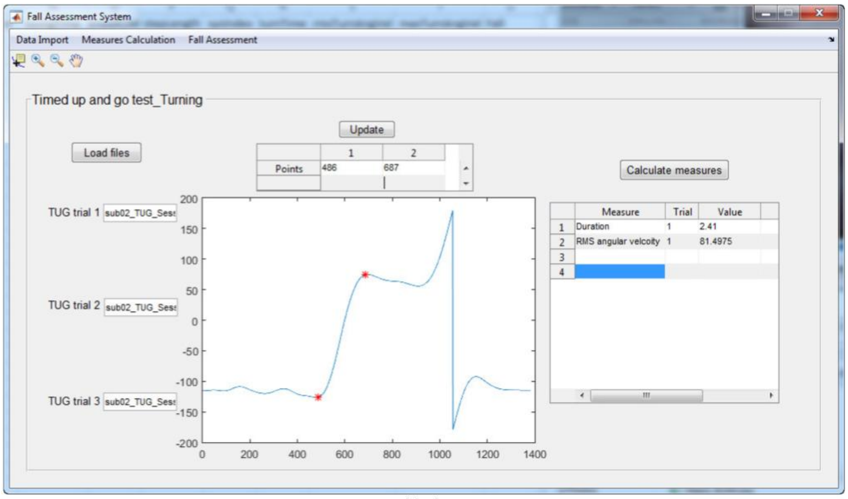


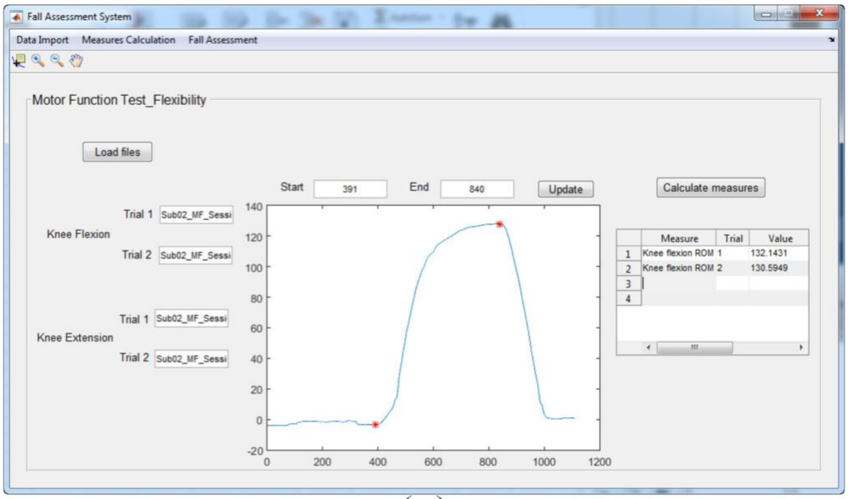
FIGURE 6.5: The operations of calculating sensory integration measures (a); limits of stability measures (b); sit-to-stand five times measures (c).



(a)



(b)



(c)

FIGURE 6.6: The operations of calculating magnitude and gait measures in timed up and go test (a); turning measures in timed up and go test (b); flexibility measures in timed up and go test (c).

In addition to measures derived from inertial sensors, some other measures were not generated from inertial sensors, such as functional reach distance and information processing speed. These measures are necessary and needed to be manually input into the system for fall classification and evaluation. Figure 6.7 shows the interface to input measures to the system. These measures included maximal muscular strengths in the motor function test, reaction test measures, short FES-I score, functional reach distance in forward, right and left directions, and additional basic information about the participant.

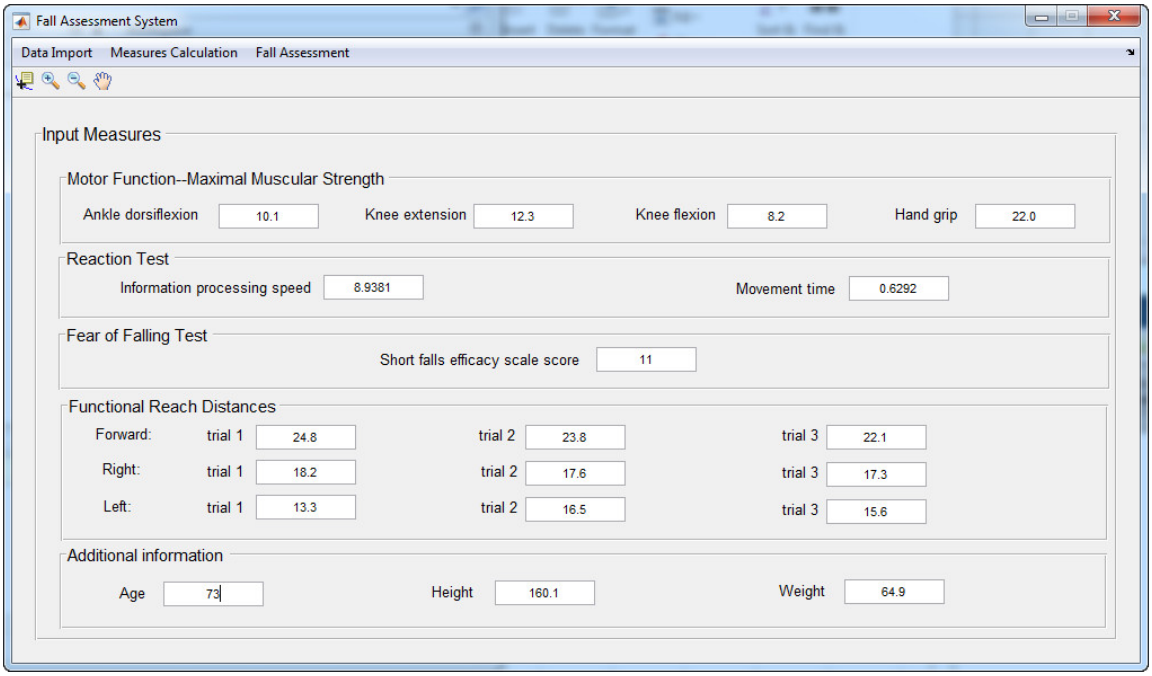


FIGURE 6.7: The interface of inputting additional measures.

Figure 6.8 shows the interface of fall risk assessment functions, which contained fall classification and evaluation. In terms of the fall classification, users selected a fall classification model and then the classification results were shown in the textbox. In terms of the fall evaluation, if old people were detected to be at high fall risk from the results of the fall classification, the decision tree and the profile graph showed the possible causes of high fall risks. Our proposed method combined the results from the decision tree and profile graph to generate the overall results. For example, when the classification and regression model was chosen for a participant, the results showed that the participant's probability of falling was 0.90, which indicated high fall risks. Then the "Decision Tree" button was clicked to check the causes of high fall risks based on the CART model, showing a poor central nervous system and relatively high fear of falling (Figure 6.9). Clicking the "Profile Graph" button allowed the user to examine the causes of high fall risk using the profile assessment method (Figure 6.9). The results showed that a poor central nervous system was the factor and poor gait stability was a potential factor. Finally, clicking the "Combined Method" button revealed the overall results (Figure 6.10). It showed that a poor central nervous system was the main cause of high fall risks, and in addition, relatively high fear of falling and poor gait stability were also indicated as potential factors that might cause high fall risks.

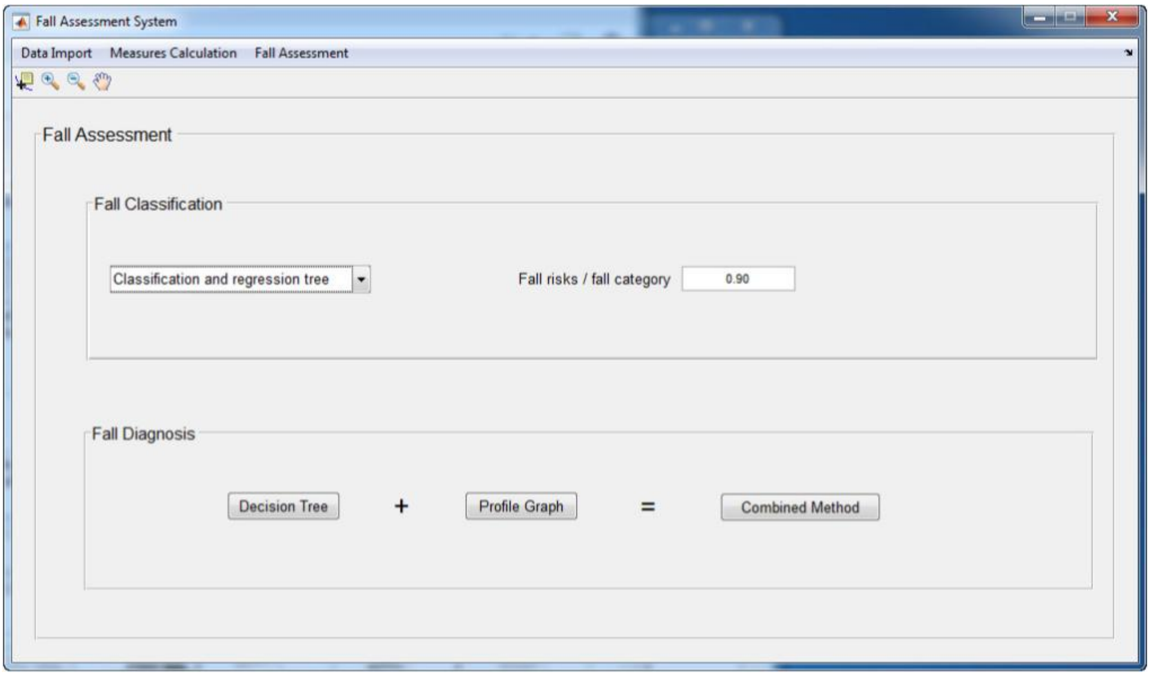
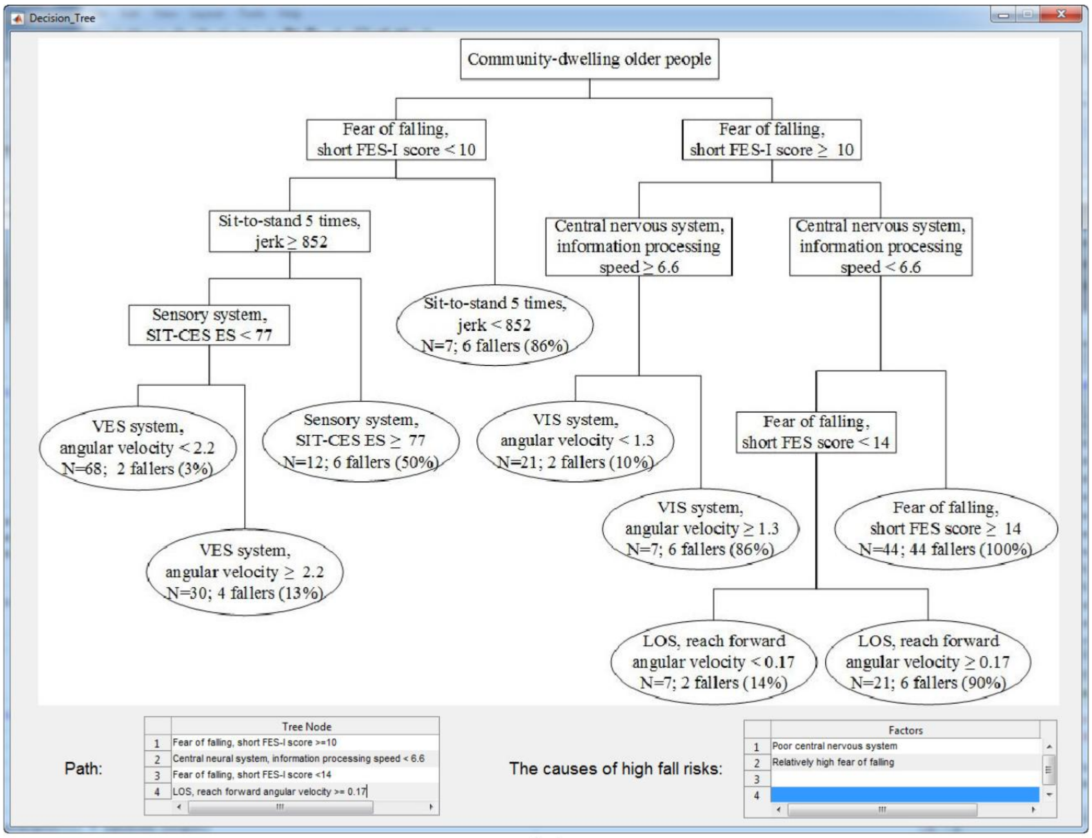
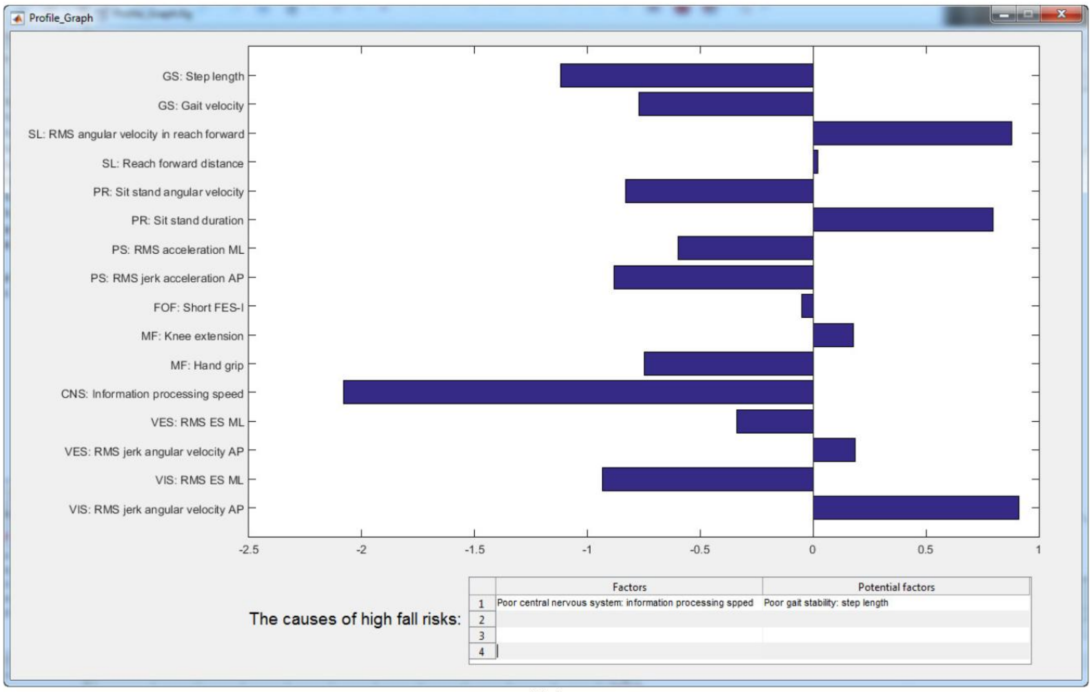


FIGURE 6.8: The typical example of fall risk assessment.



(a)



(b)

FIGURE 6.9: The typical example of identifying the causes of high fall risks: (a) the CART model; (b) profile assessment method.

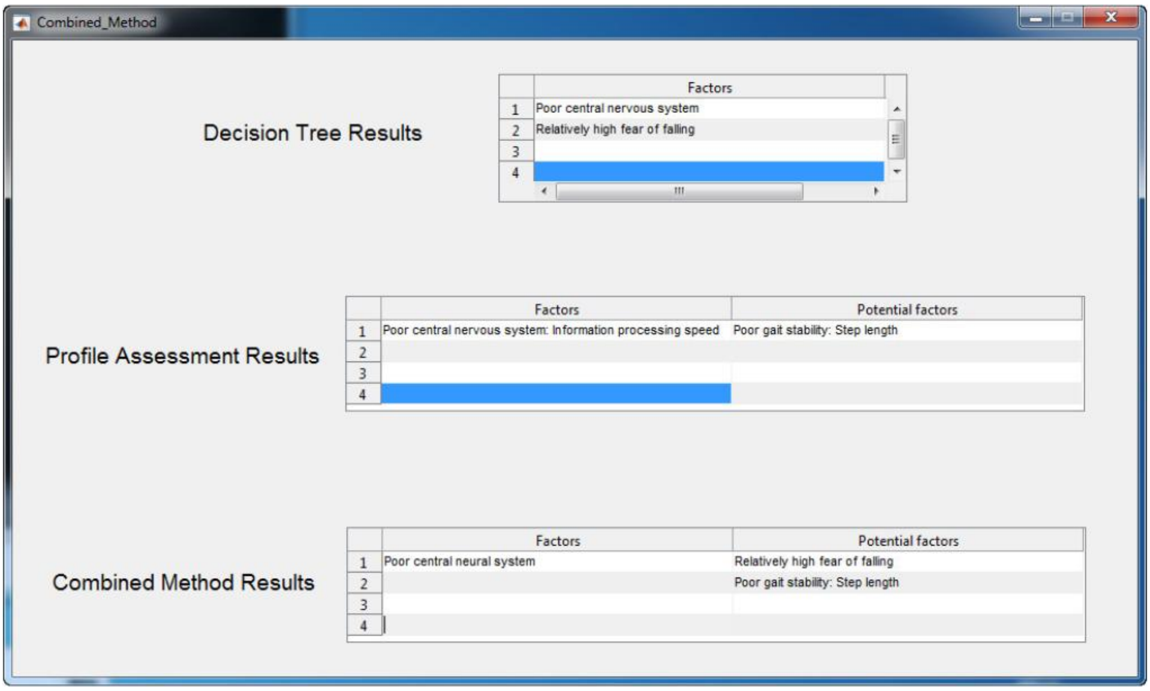


FIGURE 6.10: The typical example of identifying the causes of high fall risks using combined method.

6.5 Discussion

In this chapter, we developed an inertial sensor based prototype system for fall risk assessment. Table 6.2 presents a list of available systems or products related to fall risk assessment. We compared our system with current products in terms of functions, portability and cost.

TABLE 6.2: Current systems or products on fall risk assessment. ∗ represents the estimated price in terms of functions.

Products	***Company***	***Functions***	***Price($)***
PROPERIO Reactive Balance System	PROPRIO	1.Balance evaluation; 2.Proprioception training; 3.Weight bearing range of motion exercises; 4.Stabilization muscles strengthening.	∼ 50,000 ∗
Force plate	AMTI	1. Human gait studies; 2. Balance assessment and training.	30,000 ∼ 50,000
Balance Master System	NeuroCom	1. Peripheral/central vestibular deficits; 2. Central nervous system disorders; 3. Compensated peripheral vestibular deficits; 4. Metabolic diseases affecting balance; 5. Lower extremity injuries.	80,000 ∼ 100,000
Balance Balance System SD and Biosway	Biodex	1. Fall risk screening and conditioning; 2. Neurorehabilitation.	∼ 50,000
Sway balance–APP on iPhone	Sway medical	1. Sway balance; 2. Sway's simple reaction time.	4.25 per profile
D+R balance–APP on iPhone	D R Medical	1. Assess postural sway; 2. Peripheral vestibular function by Unterberger test	29.99
Fall prevention–APP on iPhone	EIM (Evidence In Motion)	APP is based on the STEADI (Stopping Elderly Accidents, Deaths and Injuries) Tool Kit.	4.99
Geriatric APP–APP on iPhone	Doctoc	The interactive scales available in Geriatric care: Abbreviated Mental Test Score, Geriatric Depression Scale, Barthel ADL Rating Scale, Elderly Mobility Scale, BERG Scale.	Free

Our system first evaluated the fall related factors of physiological functions, psychological functions, and integrated functions in the human balance system through a test protocol. However, most current systems only measured small parts of risk factors of falls. For example, the PROPERIO Reactive Balance System assesses the performance of postural sway, range of motion, and muscular strength. These factors were also included in physiological functions of our system. The Balance Master System only evaluated the vestibular deficit, central nervous system disorder, metabolic diseases and lower extremity injuries. Furthermore, our system also included the methods for classifying fallers and non-fallers and identifying the underlying causes of high risks of falling. In the existing systems or products, some included the functions of fall classification. For example, Balance System SD and BioSway included the function of fall risk screening and conditioning. Some questionnaires or clinical test can also be used to classify fallers and non-fallers, such as the Barthel Activity Daily Live (ADL) Rating Scale and Berg Balance Scale. In terms of identifying the underlying causes of high risks of falling, current existing systems also could examine the abnormal performance of many factors such as range of motion in PROPERIO Reactive Balance System, vestibular deficits and central nervous system disorder in the Balance Master System.

Looking at these previously developed systems, some showed good functionality. However, the equipment used in the PROPERIO Reaction Balance System, force plate, Balance Master System, and Balance System SD and BioSway was cumbersome and required a large space. Meanwhile, there were other products used the iPhone as their platform which-although portable-but unfortunately leads to limited functions. In our system, sensing technology was utilized to collect data while participants performed the tests, hence the inertial sensors were small and portable for practical application. Therefore, considering functionality and portability aspects, our system not only offers good functions, but is also portable.

Moreover, the total cost of our system was around US$2698, including 5 Shimmer sensors, one base and one Bluetooth USB adapter. This amount is much cheaper than PROPERIO Reaction Balance System, force plate, Balance Master System, and Balance System SD and BioSway, which cost at least US$ 30,000. The iPhone based APP was very cheap (even free) but the functions offered were extremely limited. Therefore, in addition to the good functions provided, our system costs significantly lower than other existing systems. The developed system could be used to identify the underlying causes of high fall risks. Since the system cost is not cheap for individuals, the system could be affordable to the hospitals, some health centers or research centers.

In the test protocol, among 7 tests, most tests used inertial sensors, including sensory integration test, limits of stability test, sit-to-stand five times test, timed up and go test, and range of motion in motor function test. Sensory integration test and limits of stability test only used the sensor attached on the pelvis and sit-to-stand five times only used the sensor attached on the right upper leg. The sensors on the lower and upper legs were used to measure the range of motion in motor function test. Only timed up and go test used 5 sensors. In the measures of timed up and go test, only gait symmetry needed four sensors on left and right upper and lower legs. From the results, the gait symmetry was not significant on distinguishing fallers and non-fallers. Other measures could be generated from one or two sensors. So it is possible to reduce 5 sensors to 3 sensors. The sensors' locations are the pelvis, right upper leg and right lower leg.

Some limitations were still existing in our system development. First, even though our software can perform data analysis, it lacks of the ability to control the inertial sensors for data acquisition, while data streaming functions were done by the software from the sensor company (Shimmer Inc.). So users had to operate two softwares for collecting and analyzing data, which was inconvenient for the users. Also, due to this limitation, there was no real-time data analysis function. In the future, the software should be improved to incorporate full functions of data collection and analysis. Additionally, users had to double check the important feature points auto-detected by developed algorithms before measures calculation to minimize the possible errors/uncertainties. It would be trivial for users to do so one by one. Later, one function can be developed to calculate all measures directly and advanced algorithms should be also designed to identify possible errors on feature points to remind users.

6.6 Conclusion

In this chapter, a fall risk assessment system was developed as an implementation of proposed methods for fall classification and evaluation. Compared with existing systems or products, our developed system provides powerful functions for systematically evaluating fall risk factors and identifying the underlying causes of high fall risks. Our system is also portable which consequently enables it to be widely used at any time and in any place. Furthermore, the whole system was significantly cheaper than other existing systems. Therefore, our developed system offers good potential for future applications in assessing fall risk in older people.

Chapter 7

Conclusions and future work

7.1 Summary of main findings

In this study, we used inertial sensors to assess fall risk and to develop a system for older people. In order to assess fall risks, a new test protocol based on the human balance system that could cover fall-related factors systematically for identifying the underlying causes of the high risk of falls, was designed in our first study. The second study was conducted to examine the effectiveness of Hick's law based reaction test in the protocol on assessing cognitive function and fall risks. After the test protocol was validated, we conducted a large-scale experiment based on our newly-designed protocol by using inertial sensors to assess fall risks in older people. At this stage, a third study was conducted to construct various statistical models to classify fallers and non-fallers. In addition to fall classification, our fourth study was conducted to develop methods for identifying the underlying causes of the high risks of falls in older people. At last, an inertial sensor-based prototype system consisting of hardware and software was developed so the proposed methods can be used to assess fall risks in older people.

In the first study, we designed a new test protocol that covered the factors related to the human balance system. The protocol had to meet the following criteria: (1) simple and quick to administer; (2) feasible for older people to undertake; (3) valid and reliable tests for assessing corresponding risk factors; (4) provide quantitative measures, which should be mainly obtained from wearable inertial sensors. Therefore, the test protocol consisted of seven main tests, i.e., (1) the sensory integration test; (2) limits of stability; (3) sit-to-stand five times test; (4) timed up and go test; (5) motor function test; (6) reaction test; and (7) short falls efficacy scale international. In the fall-related factors, the visual system, vestibular system, somatosensory system, biomechanical constraints, and sensory orientation were evaluated by the sensory integration test. The central nervous system of cognitive function and its motor system were assessed in a reaction test and a motor function test, respectively. Fear of falling was assessed through the questionnaire of short falls efficacy scale. Both anticipatory postural adjustments and postural response were measured in the test that involved sit-to-stand five times. Evaluations of stability limits and stability in gait were conducted in limits of stability test and the timed up and go test, respectively.

The findings from the second study indicated that the speed of processing information was an important biomarker for falling, and the reaction test APP was sensitive to fall risk in older people. Fallers showed significantly lower information-processing speed than non-fallers. However, there was no significant difference on movement time between fallers and non-fallers. In the test, information processing speed was correlated with the cognitive function. Previous studies have reported that fallers have much poorer cognitive function than non-fallers (Muir et al., 2012). However, movement time was more associated with motor control function.

The third study indicated that our newly-designed test protocol was effective on classifying fallers and non-fallers. First, through the statistical analysis of measures derived from the tests, fallers were found to have significantly poorer physiological, psychological, and integrated functions than non-fallers. Furthermore, six typical statistical models with different flexibilities were developed to classify fallers and non-fallers based on significant measures in the tests and the fall histories. Among these models, three highly-flexible models, i.e., support vector machine radial basis function, random forest, and boosted tree models, had excellent accuracy but poor interpretability because the models functioned essentially as 'black boxes.' The logistic regression, linear discriminant analysis, and classification and regression tree models had relatively lower accuracy than the highly-flexible models, but they had good interpretability in terms of the relationship between the risk factors and the type of older person, i.e., faller or non-faller. Depending on the research requirements of model interpretability and accuracy, proper models could be chosen for practical application.

The findings from the fourth study proved that our proposed method, which combined classification and regression tree (CART) model with the profile assessment could be a significant advancement in identifying the underlying causes of high fall risks in order to prevent falls. First, in our model, we selected measurable, modifiable, and important fall-related factors based on the human balance system. Once the factors were identified as the causes of high risk of falling, a customized rehabilitation program could be designed for older people to reduce their risks of falling more effectively. The CART model identified the causes of the high risks of falling by building tree-based relationships between the risk factors for falling and the types of falls. In addition, the profile assessment method was proposed to identify the causes of high fall risks. Different from the CART model, this method examined the abnormal factors based on a normal distribution of the population. Compared with the profile assessment method, the CART model had the advantages of using the relationships between fall factors and fall type. The profile assessment method was effective on examining abnormal risk factors but had a weak relationship with the types of falls. The combination of the two methods could provide a better method of identifying the causes of falls.

The fifth study indicated that our inertial sensor-based prototype system could be very promising when compared with other available systems in terms of powerful functions, portability, and low-cost for assessing the fall risks of older people. First, the system covered the evaluations of fall risk-related factors systematically considering the human balance system, ranging from each individual system to integrated functions on performing certain tasks. Also advanced fall classification and diagnostic methods were embedded in the system to identify the underlying causes of high fall risks. In addition, since the hardware was combined with wearable inertial sensors, the system could be used extensively anytime and anywhere. Importantly, the cost of a system was significantly lower than current fall-risk assessment systems.

7.2 Limitations

There were several limitations inherent in this study. First, the risk factors associated with falls are classified as intrinsic and extrinsic factors (Lajoie and Gallagher, 2004). Our proposed methods would be unable to determine several of these factors, e.g., they could not determine whether the falls that occurred were influenced by extrinsic factors or not, and they could not detect the causes of high risks for falls in which any extrinsic factors were involved. We only evaluated fall-risk factors based on human balance system under normal environmental conditions. The environmental factors could affect balance ability and result in falls. For example, the poor lighting could reduce the performance of vision system and cause falls. The second limitation is that only older Korean females were recruited for the experiment to avoid biased results that might be caused from the effect of gender. Therefore, there is a need for further investigation to determine whether our study would be applicable for the older male population. Third, our study used the history of falls as a criterion to identify fallers and non-fallers. In order to predict the risk of falling, it would be better to choose future falls as the criteria, since fall experience can result in physiological consequences, such as injuries and psychological effects, such as the fear of falling. Fourth, we proposed methods to identify the underlying causes of high risk of falling. However, a standard reference has not been developed to validate the methods used in the current study. An evaluation from a doctor at a hospital, for instance, could be used to validate the results of our proposed methods. Last but not least, our developed software mainly focused on data analysis, not the data acquisition. Additional sensing data acquisition function was realized through another software from the sensor company (Shimmer Inc.). It could be inconvenient for customers to use our prototype system.

7.3 Future work

Considering limitations in the current study, several studies can be conducted in the future. First, the environmental factors are generally uncontrollable. In order to consider the environmental factors into fall risk assessment, it is necessary to identify some controllable environmental factors. For example, as the elderly stay at home most time, it is possible to add the lightness and floor roughness at home as the factors to assess fall risks. Second, prospective falls of each participant can be collected through a follow-up study to evaluate the effectiveness of the proposed methods on future fall risks. Third, in our test protocol, even though most tests were evaluated by an inertial sensor based system, a few tests were assessed by other methods, such as fear of falling using a paper-based survey questionnaire, reaction test using iPad, and muscle strength using hand-held dynamometer. In the future, all these tests in the protocol will be integrated into one system. Lastly, the real-time fall assessment system should be developed for future applications, in which the software should be improved to incorporate data acquisition and data analysis functions together as a complete system.

Appendix A

Statistical analysis results of measures derived from tests in the protocol

TABLE A.1: Significance of vision (VIS) measures on differentiating fallers and non-fallers in sensory integration test. acc: acceleration; angVel: angular velocity; AP: anteroposterior; AUC: area under ROC curve; ES: equilibrium score; ML: mediolateral; PSD: power spectral density; rms: root mean square. Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Measures	***t test p value (sign)***	***Effect size***	***AUC***	***AUC pValue***
rms acc AP	0.7428	0.0404	0.5004	0.9903
rms acc ML	0.2780	0.1348	0.5408	0.2525
rms angVel AP	0.0069 (+)	0.3529	0.5835	0.0201
rms angVel ML	0.2724	0.1379	0.5517	0.1518
ESAP	0.4506	0.0951	0.5467	0.1990
ESML	0.0007 (-)	0.4349	0.6148	0.0008
Jerk acc AP	0.0080 (+)	0.3371	0.6090	0.0020
Jerk acc ML	0.0001 (+)	0.5240	0.6224	0.0005
Jerk angVel AP	0.0007 (+)	0.4602	0.5775	0.0356
Jerk angVel ML	0.0205 (+)	0.3041	0.603	0.0048
PSD acc AP	0.1232	0.2038	0.5207	0.5825
PSD acc ML	0.0028 (+)	0.3894	0.6090	0.0022
PSD angVel AP	0.0024 (+)	0.4001	0.6073	0.003
PSD angVel ML	0.3549	0.1195	0.5135	0.7147

TABLE A.2: Significance of vestibule (VES) measures on differentiating fallers and non-fallers in sensory integration test. acc: acceleration; angVel: angular velocity; AUC: area under ROC curve; AP: anteroposterior; ES: equilibrium score; ML: mediolateral; PSD: power spectral density; rms: root mean square.Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Measures	***t test p value (sign)***	***Effect size***	***AUC***	***AUC pValue***
rms acc AP	0.3802	0.1084	0.4836	0.6497
rms acc ML	0.2094	0.1550	0.5512	0.1516
rms angVel AP	0.0004 (+)	0.4742	0.6066	0.0030
rms angVel ML	0.2019	0.1630	0.5518	0.1556
ES AP	0.6853	0.0512	0.5233	0.5245
ES ML	0.0056 (-)	0.3523	0.5995	0.0050
Jerk acc AP	0.0199 (+)	0.2998	0.6030	0.0040
Jerk acc ML	0.0024 (+)	0.4037	0.5945	0.0094
JerkangVelAP	0.0011 (+)	0.4434	0.5622	0.0924
Jerk angVel ML	0.1095	0.2100	0.5655	0.0742
PSD acc AP	0.4283	0.1018	0.5165	0.6565
PSD acc ML	0.0031 (+)	0.3857	0.5979	0.0068
PSD angVel AP	0.0021 (+)	0.4143	0.5880	0.0165
PSD angVel ML	0.3721	0.1164	0.5237	0.5259

TABLE A.3: Significance of somatosensory (SOM) measures on differentiating fallers and non-fallers in sensory integration test. acc: acceleration; angVel: angular velocity; AUC: area under ROC curve; AP: anteroposterior; ES: equilibrium score; ML: mediolateral; PSD: power spectral density; rms: root mean square.Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Measures	***t test p value (sign)***	***Effect size***	***AUC***	***AUC p value***
rms acc AP	0.6304	0.0605	0.4963	0.9200
rms acc ML	0.1239	0.1942	0.5518	0.1515
rms angVel AP	0.3568	0.1176	0.4969	0.9338
rms angVel ML	0.1325	0.1860	0.5494	0.1682
ES AP	0.6750	0.0522	0.4916	0.8180
ES ML	0.5626	0.0757	0.5218	0.5618
Jerk acc AP	0.6048	0.0658	0.5380	0.2999
Jerk acc ML	0.7725	0.0362	0.5054	0.8813
Jerk angVel AP	0.6972	0.0487	0.5032	0.9294
Jerk angVel ML	0.2437	0.1458	0.5541	0.1338
PSD acc AP	0.6034	0.0671	0.5101	0.7844
PSD acc ML	0.2957	0.1313	0.5437	0.2290
PSD angVel AP	0.9165	0.0131	0.5046	0.8998
PSD angVel ML	0.7517	0.0405	0.5231	0.5325

TABLE A.4: Significance of sensory system measures on differentiating fallers and non-fallers in sensory integration test. acc: acceleration; angVel: angular velocity; AUC: area under ROC curve; AP: anteroposterior; ES: equilibrium score; ML: mediolateral; PSD: power spectral density; rms: root mean square.Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Measures	***t test p value (sign)***	***Effect size***	***AUC***	***AUC pValue***
rms acc AP	0.0322 (+)	0.3782	0.5972	0.0499
rms acc ML	0.0042 (+)	0.5174	0.6497	0.0019
rms angVel AP	0.1850	0.2424	0.5543	0.2942
rms angVel ML	0.0160 (+)	0.4464	0.6126	0.0271
ES AP	0.0468	0.3529	0.5941	0.0599
ES ML	0.0102 (-)	0.4701	0.6394	0.005
Jerk acc AP	0.0556	0.3679	0.5883	0.0979
Jerk acc ML	0.1465	0.2785	0.5569	0.2856
Jerk angVel AP	0.0923	0.3250	0.578	0.1438
Jerk angVel ML	0.0682	0.3476	0.6018	0.0572
PSD acc AP	0.0174 (+)	0.4287	0.6217	0.0133
PSD acc ML	0.0008 (+)	0.6363	0.6708	0.0004
PSD angVel AP	0.0504	0.3707	0.5954	0.0655
PSD angVel ML	0.0022 (+)	0.5785	0.6435	0.0033

TABLE A.5: Significance of central neural system measures on differentiating fallers and non-fallers in the reaction test. AUC: area under ROC curve.Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Measure	***t test p value (sign)***	***Effect size***	***AUC***	***AUC p value***
Movement time	0.1800	0.2893	0.5655	0.2930
Information Processing speed	$<$.0001 (-)	1.1708	0.7955	$<$.0001

TABLE A.6: Significance of measures on differentiating fallers and non-fallers in motor function test. AUC: area under ROC curve. Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Measure	***t test p value (sign)***	***Effect size***	***AUC***	***AUC p value***
Range of knee extension	<.0001 (-)	0.4212	0.6178	<.0001
Range of knee flexion	0.0068 (-)	0.2764	0.5815	0.0049
Max ankle dorsiflexion force / weight	0.1619	0.1735	0.4637	0.3102
Max knee extension force / weight	0.0002 (-)	0.4622	0.6253	0.0002
Max knee flexion force / weight	0.0013 (-)	0.3977	0.6012	0.0036
Max hand grip force / weight	0.0001 (-)	0.4972	0.6336	0.0001

TABLE A.7: Significance of fear of falling measures on differentiating fallers and non-fallers in falls efficacy scale. Short FES-I: short falls efficacy scale international; AUC: area under ROC curve. Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Measure	***t test p value (sign)***	***Effect size***	***AUC***	***AUC p value***
short FES-I	<.0001 (+)	1.5774	0.8677	<.0001

TABLE A.8: Significance of postural sway measures on differentiating fallers and non-fallers at the condition of eyes open and sway surface in sensory integration test. acc: acceleration; angVel: angular velocity; AUC: area under ROC curve; AP: anteroposterior; ES: equilibrium score; ML: mediolateral; PSD: power spectral density; rms: root mean square.Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Category	***Measures***	***t test p value (sign)***	***Effect size***	***AUC***	***AUC p value***
Time domain	rms acc AP	0.0032 (+)	0.3687	0.6084	0.0018
	rms acc ML	0.0002 (+)	0.4890	0.6258	0.0003
	rms angVel AP	0.0379	0.2688	0.5544	0.1356
	rms angVel ML	0.0006 (+)	0.4490	0.6074	0.0028
	rms Jerk acc AP	0.0015 (+)	0.4070	0.6104	0.0016
	Jerk acc ML	<.0001 (+)	0.5445	0.6374	0.0001
	Jerk angVel AP	0.0059 (+)	0.3623	0.5926	0.0110
	Jerk angVel ML	0.0076 (+)	0.3544	0.5759	0.0377
	ES AP	0.0056 (-)	0.3753	0.5754	0.0451
	ES ML	0.1323	0.1931	0.5703	0.0580
Frequency domain	median Frequency acc AP	0.4737	0.0897	0.5340	0.3458
	median Frequency acc ML	0.0353	0.2579	0.5536	0.1331
	median Frequency angVel AP	0.2104	0.1533	0.4752	0.4895
	median Frequency angVel ML	0.2689	0.1418	0.5510	0.1686
	PSD acc AP	<.0001 (+)	0.5531	0.6322	0.0002
	PSD acc ML	0.0001 (+)	0.5461	0.6245	0.0005
	PSD angVel AP	0.0426 (+)	0.2645	0.5732	0.0435
	PSD angVel ML	0.0009 (+)	0.4412	0.6072	0.0029
	Centroidal Frequency acc AP	0.0303	0.2706	0.5680	0.0545
	Centroidal Frequency acc ML	0.0778	0.2151	0.5575	0.1016
	Centroidal Frequency angVel AP	0.2226	0.1514	0.5545	0.1280
	Centroidal Frequency angVel ML	0.1990	0.1553	0.5243	0.4923

TABLE A.9: Significance of measures on differentiating fallers and non-fallers in limits of stability test. angVel: angular velocity; AUC: area under ROC curve; AP: anteroposterior; ES: equilibrium score; ML: mediolateral; rms: root mean square.Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Category	*Measures*	*t test p value (sign)*	*Effect size*	*AUC*	*AUC p value*
Reach forward	Reach distance	<.0001 (-)	0.5608	0.6613	<.0001
	rms angVel AP	0.0216	0.2287	0.5625	0.0297
	Jerk angVel AP	<.0001 (-)	0.4404	0.5858	0.0034
Reach right	Reach distance	<.0001 (-)	0.4289	0.6620	<.0001
	rms angVel ML	0.0002 (-)	0.3757	0.6078	0.0001
	Jerk AngVel ML	<.0001 (-)	0.5110	0.6201	<.0001
Reach left	Reach distance	0.0012 (-)	0.3296	0.5998	0.0005
	rms angVel ML	0.6620	0.0443	0.5043	0.8850
	Jerk angVel ML	0.0001 (-)	0.3913	0.5862	0.0028

TABLE A.10: Significance of measures on differentiating fallers and non-fallers in sit-to-stand five times test. angVel: angular velocity; AUC: area under ROC curve; rms: root mean square. Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Category	***Measure***	***t test p value (sign)***	***Effect size***	***AUC***	***AUC p value***
sit-stand-sit	Duration	0.0001 (+)	0.4981	0.6254	0.0004
	rms angVel	0.0007 (-)	0.4229	0.6228	0.0004
	Jerk	0.0041 (-)	0.3606	0.6150	0.0011
sit-stand	Duration	<.0001 (+)	0.6045	0.6565	<.0001
	rms angVel	0.0001 (-)	0.4975	0.6425	<.0001
	Jerk	0.0006 (-)	0.4343	0.6294	0.0002
stand-sit	Duration	0.0060 (+)	0.3504	0.5937	0.0083
	rms angVel	0.0067 (-)	0.3387	0.6015	0.0036
	Jerk	0.0123 (-)	0.3142	0.6004	0.0049

TABLE A.11: Significance of measures on differentiating fallers and non-fallers in timed up and go test. acc: acceleration; angVel: angular velocity; AUC: area under ROC curve; AP: anteroposterior; ES: equilibrium score; ML: mediolateral; V: vertical; rms: root mean square. Sign: plus (+) represents the measure value of faller higher than non-faller; minus (-) represents the measure value of faller lower than non-faller.

Cateory	***Subcategory***	***measure***	***t test p value (sign)***	***Effect size***	***AUC***	***AUC p value***
Walk	Amplitude of raw data	rms acc AP	0.0001 (-)	0.4000	0.6116	0.0001
		rms acc ML	0.7691	0.0299	0.5031	0.9147
		rms acc V	0.1134	0.1666	0.4702	0.3232
		rms angVel AP	0.0019 (-)	0.3234	0.5805	0.0060
		rms angVel ML	0.0001 (-)	0.4026	0.6007	0.0004
		rms angVel V	<.0001 (-)	0.4316	0.6228	<.0001
	Gait pattern	gait velocity	<.0001 (-)	0.4435	0.6258	<.0001
		stride time	0.0003 (+)	0.3803	0.5885	0.0028
		stride length	<.0001 (-)	0.5578	0.6703	<.0001
		Single support	0.0001 (-)	0.4108	0.6203	<.0001
		range of motion on knee joint	0.5693	0.0587	0.4731	0.3624
		Gait symmetry	0.1123	0.1627	0.5538	0.0668
Turn	Amplitude of raw data	rms angVel V	0.0210 (-)	0.2410	0.5576	0.0518
		max angVel V	0.0065 (-)	0.3888	0.5613	0.0425
	Time	turn time	0.2665	0.1149	0.5227	0.4417

Bibliography

Alexander, N. B. and Hausdorff, J. M. (2008). Guest editorial linking thinking, walking, and falling. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 63(12):1325–1328.

Ambrose, A. F., Paul, G., and Hausdorff, J. M. (2013). Risk factors for falls among older adults: a review of the literature. *Maturitas*, 75(1):51–61.

Anderson, J. A. (1995). *An introduction to neural networks*. MIT press.

Baker, J. (2003). Balance master® system operator's manual version 8.1. clackamas: Neurocom® international.

Baloh, R. W., Enrietto, J., Jacobson, K. M., and Lin, A. (2001). Age-related changes in vestibular function. *Annals of the New York Academy of Sciences*, 942(1):210–219.

Beauchet, O., Fantino, B., Allali, G., Muir, S., Montero-Odasso, M., and Annweiler, C. (2011). Timed up and go test and risk of falls in older adults: a systematic review. *The journal of nutrition, health & aging*, 15(10):933–938.

Behrman, A. L., Light, K. E., Flynn, S. M., and Thigpen, M. T. (2002). Is the functional reach test useful for identifying falls risk among individuals with parkinson's disease? *Archives of physical medicine and rehabilitation*, 83(4):538–542.

Bell, A. J., Talbot-Stern, J. K., and Hennessy, A. (2000). Characteristics and outcomes of older patients presenting to the emergency department after a fall: a retrospective analysis. *The Medical Journal of Australia*, 173(4):179–182.

Berg, K., Wood-Dauphine, S., Williams, J., and Gayton, D. (1989). Measuring balance in the elderly: preliminary development of an instrument. *Physiotherapy Canada*, 41(6):304–311.

Berg, K. O., Maki, B. E., Williams, J. I., Holliday, P. J., and Wood-Dauphinee, S. L. (1992). Clinical and laboratory measures of postural balance in an elderly population. *Archives of physical medicine and rehabilitation*, 73(11):1073–1080.

Bongue, B., Dupré, C., Beauchet, O., Rossat, A., Fantino, B., and Colvez, A. (2011). A screening tool with five risk factors was developed for fall-risk prediction in community-dwelling elderly. *Journal of clinical epidemiology*, 64(10):1152–1160.

Boswell, E. B. and Stoudemire, A. (1996). Major depression in the primary care setting. *The American journal of medicine*, 101(6):3S–9S.

Buatois, S., Miljkovic, D., Manckoundia, P., Gueguen, R., Miget, P., Vançon, G., Perrin, P., and Benetos, A. (2008). Five times sit to stand test is a predictor of recurrent falls in healthy community-living subjects aged 65 and older. *Journal of the American Geriatrics Society*, 56(8):1575–1577.

Burns, A., Greene, B. R., McGrath, M. J., O'Shea, T. J., Kuris, B., Ayer, S. M., Stroiescu, F., and Cionca, V. (2010). Shimmer™–a wireless sensor platform for noninvasive biomedical research. *Sensors Journal, IEEE*, 10(9):1527–1534.

Butler, A. a., Menant, J. C., Tiedemann, A. C., and Lord, S. R. (2009). Age and gender differences in seven tests of functional mobility. *Journal of neuroengineering and rehabilitation*, 6:31.

Caby, B., Kieffer, S., de Saint Hubert, M., Cremer, G., and Macq, B. (2011). Feature extraction and selection for objective gait analysis and fall risk assessment by accelerometry. *Biomedical engineering online*, 10(1):1.

Carroll, M., Joyce, W., Brenton-Rule, A., Dalbeth, N., and Rome, K. (2013). Assessment of foot and ankle muscle strength using hand held dynamometry in patients with established rheumatoid arthritis. *Journal of foot and ankle research*, 6(Suppl 1):O4.

Casanova, J. (1992). Clinical assessment recommendations. *American Society of Hand Therapists: Chicago,*.

Centers for Disease Control and Prevention (2015). Falls among older adults: An overview. *Centers for Disease Control Injury Center, National Center for Injury Prevention and Control. Retrieved March*, 29.

Chen, J. S., March, L. M., Schwarz, J., Zochling, J., Makaroff, J., Sitoh, Y., Lau, T. C., Lord, S. R., Cameron, I. D., Cumming, R. G., et al. (2005). A multivariate regression model predicted falls in residents living in intermediate hostel care. *Journal of Clinical Epidemiology*, 58(5):503–508.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic press.

Contarino, D., Bertora, G. O., and Bergmann, J. M. (2003). Balance platform: mathematical modeling for clinical evaluation. *International Tinnitus Journal*, 9(1):23–25.

Cook, P., Exton-Smith, A., Brocklehurst, J., and Lempert-Barber, S. (1982). Fractured femurs, falls and bone disorders. *Journal of the Royal College of Physicians of London*, 16(1):45–49.

Cristianini, N. and Shawe-Taylor, J. (2000). *An introduction to support vector machines and other kernel-based learning methods*. Cambridge university press.

Davis, J., Robertson, M., Ashe, M., Liu-Ambrose, T., Khan, K., and Marra, C. (2010). International comparison of cost of falls in older adults living in the community: a systematic review. *Osteoporosis international*, 21(8):1295–1306.

Deandrea, S., Lucenteforte, E., Bravi, F., Foschi, R., La Vecchia, C., and Negri, E. (2010). Risk factors for falls in community-dwelling older people: a systematic review and meta-analysis. *Epidemiology*, 21(5):658–668.

Deery, H. A., Day, L. M., and Fildes, B. N. (2000). An impact evaluation of a falls prevention program among older people. *Accident Analysis & Prevention*, 32(3):427–433.

Delbaere, K., Close, J. C., Heim, J., Sachdev, P. S., Brodaty, H., Slavin, M. J., Kochan, N. A., and Lord, S. R. (2010). A multifactorial approach to understanding fall risk in older people. *Journal of the American Geriatrics Society*, 58(9):1679–1685.

Delbaere, K., Close, J. C., Taylor, M., Wesson, J., and Lord, S. R. (2013). Validation of the iconographical falls efficacy scale in cognitively impaired older people. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 68(9):1098–1102.

Delbaere, K., Smith, S. T., and Lord, S. R. (2011). Development and initial validation of the iconographical falls efficacy scale. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 66(6):674–680.

Demura, S.-i. and Yamada, T. (2007). Simple and easy assessment of falling risk in the elderly by functional reach test using elastic stick. *The Tohoku journal of experimental medicine*, 213(2):105–111.

Doheny, E. P., Fan, C. W., Foran, T., Greene, B. R., Cunningham, C., and Kenny, R. A. (2011). An instrumented sit-to-stand test used to examine differences between older fallers and non-fallers. In *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pages 3063–3066. IEEE.

Duncan, P. W., Weiner, D. K., Chandler, J., and Studenski, S. (1990). Functional reach: a new clinical measure of balance. *Journal of gerontology*, 45(6):M192–M197.

Duncan, R. P., Leddy, A. L., and Earhart, G. M. (2011). Five times sit-to-stand test performance in parkinson's disease. *Archives of physical medicine and rehabilitation*, 92(9):1431–1436.

Dunlop, D. D., Manheim, L. M., Sohn, M.-W., Liu, X., and Chang, R. W. (2002). Incidence of functional limitation in older adults: the impact of gender, race, and chronic conditions. *Archives of physical medicine and rehabilitation*, 83(7):964–971.

Eliana, F., Stefania, B., Gianpiero, G., Dario, A., Antonio, C., et al. (2009). The use of rubber foam pads and "sensory ratios" to reduce variability in static posturography assessment. *Gait & posture*, 29(1):158–160.

Elith, J., Leathwick, J. R., and Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology*, 77(4):802–813.

Exton-Smith, A. (1997). Functional consequences of ageing: clinical manifestations: In: Exton-smith an, grimley evans j eds. care of the elderly: Meeting the challenge of dependency.

Fluss, R., Faraggi, D., and Reiser, B. (2005). Estimation of the youden index and its associated cutoff point. *Biometrical Journal*, 47(4):458–472.

Franzen, H., Hunter, H., Landreth, C., Beling, J., Greenberg, M., and Canfield, J. (1999). Comparison of functional reach in fallers and nonfallers in an independent retirement community. *Physical & Occupational Therapy in Geriatrics*, 15(4):33–40.

Friedman, J., Hastie, T., and Tibshirani, R. (2001). *The elements of statistical learning*, volume 1. Springer series in statistics Springer, Berlin.

Friedman, S. M., Munoz, B., West, S. K., Rubin, G. S., and Fried, L. P. (2002). Falls and fear of falling: which comes first? a longitudinal prediction model suggests strategies for primary and secondary prevention. *Journal of the American Geriatrics Society*, 50(8):1329–1335.

Fuller, G. F. (2000). Falls in the elderly. *American family physician*, 61(7):2159–68.

Ganz, D. A., Bao, Y., Shekelle, P. G., and Rubenstein, L. Z. (2007). Will my patient fall? *Jama*, 297(1):77–86.

Girardi, M., Konrad, H. R., Amin, M., and Hughes, L. F. (2001). Predicting fall risks in an elderly population: computer dynamic posturography versus electronystagmography test results. *The Laryngoscope*, 111(9):1528–1532.

Grabiner, M. D. and Jahnigen, D. (1992). Modeling recovery from stumbles: preliminary data on variable selection and classification efficacy. *Journal of the American Geriatrics Society*, 40(9):910–913.

Granata, K. P. and Lockhart, T. E. (2008). Dynamic stability differences in fall-prone and healthy adults. *Journal of Electromyography and Kinesiology*, 18(2):172–178.

Greenberg, S. A. (2011). Assessment of fear of falling in older adults: The falls efficacy scale-international (fes-i). *Disability and Rehabilitation*, 29(2):155–162.

Greene, B. R., Donovan, A. O., Romero-Ortuno, R., Cogan, L., Scanaill, C. N., Kenny, R., et al. (2010a). Quantitative falls risk assessment using the timed up and go test. *Biomedical Engineering, IEEE Transactions on*, 57(12):2918–2926.

Greene, B. R., McGrath, D., O'Donovan, K. J., O'Neill, R., Burns, A., and Caulfield, B. (2010b). Adaptive estimation of temporal gait parameters using body-worn gyroscopes. In *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, pages 1296–1299. IEEE.

Greene, B. R., McGrath, D., Walsh, L., Doheny, E. P., McKeown, D., Garattini, C., Cunningham, C., Crosby, L., Caulfield, B., and Kenny, R. A. (2012). Quantitative falls risk estimation through multi-sensor assessment of standing balance. *Physiological measurement*, 33(12):2049.

Greiner, M., Pfeiffer, D., and Smith, R. (2000). Principles and practical application of the receiver-operating characteristic analysis for diagnostic tests. *Preventive veterinary medicine*, 45(1):23–41.

Gurley, R. J., Lum, N., Sande, M., Lo, B., and Katz, M. H. (1996). Persons found in their homes helpless or dead. *New England Journal of Medicine*, 334(26):1710–1716.

Hamacher, D., Singh, N., Van Dieen, J., Heller, M., and Taylor, W. (2011). Kinematic measures for assessing gait stability in elderly individuals: a systematic review. *Journal of The Royal Society Interface*, 8(65):1682–1698.

Harvey, P. D. (2012). Clinical applications of neuropsychological assessment. *Dialogues in clinical neuroscience*, 14(1):91.

Helbostad, J. L., Taraldsen, K., Granbo, R., Yardley, L., Todd, C. J., and Sletvold, O. (2010). Validation of the falls efficacy scale-international in fall-prone older persons. *Age and ageing*, 39(2):259–259.

Herman, T., Giladi, N., and Hausdorff, J. M. (2011). Properties of the 'timed up and go'test: more than meets the eye. *Gerontology*, 57(3):203–210.

Hick, W. E. (1952). On the rate of gain of information. *Quarterly Journal of Experimental Psychology*, 4(1):11–26.

Hilbe, J. M. (2009). *Logistic regression models*. CRC Press.

Horak, F. and Hlavacka, F. (2001). Somatosensory loss increases vestibulospinal sensitivity. *Journal of neurophysiology*, 86(2):575–585.

Horak, F. B. (1997). Clinical assessment of balance disorders. *Gait & Posture*, 6(1):76–84.

Horak, F. B. (2006). Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls? *Age and ageing*, 35(suppl 2):ii7–ii11.

Horak, F. B., Shupert, C. L., and Mirka, A. (1989). Components of postural dyscontrol in the elderly: a review. *Neurobiology of aging*, 10(6):727–738.

Horak, F. B., Wrisley, D. M., and Frank, J. (2009). The balance evaluation systems test (bestest) to differentiate balance deficits. *Physical therapy*, 89(5):484–498.

Horlings, C. G., van Engelen, B. G., Allum, J. H., and Bloem, B. R. (2008). A weak balance: the contribution of muscle weakness to postural instability and falls. *Nature Clinical Practice Neurology*, 4(9):504–515.

Hosmer Jr, D. W. and Lemeshow, S. (2004). *Applied logistic regression*. John Wiley & Sons.

Howcroft, J., Kofman, J., and Lemaire, E. D. (2013). Review of fall risk assessment in geriatric populations using inertial sensors. *J Neuroeng Rehabil*, 10(1):10–91.

Hyman, R. (1953). Stimulus information as a determinant of reaction time. *Journal of experimental psychology*, 45(3):188.

Inouye, S. K., Studenski, S., Tinetti, M. E., and Kuchel, G. A. (2007). Geriatric syndromes: clinical, research, and policy implications of a core geriatric concept. *Journal of the American Geriatrics Society*, 55(5):780–791.

Ishigaki, N., Kimura, T., Usui, Y., Aoki, K., Narita, N., Shimizu, M., Hara, K., Ogihara, N., Nakamura, K., Kato, H., et al. (2011). Analysis of pelvic movement in the elderly during walking using a posture monitoring system equipped with a triaxial accelerometer and a gyroscope. *Journal of biomechanics*, 44(9):1788–1792.

James, G., Witten, D., and Hastie, T. (2014). An introduction to statistical learning: With applications in r.

Jensen, A. R. and Munro, E. (1979). Reaction time, movement time, and intelligence. *Intelligence*, 3(2):121–126.

Kandel, E. R., Schwartz, J. H., Jessell, T. M., et al. (2000). *Principles of neural science*, volume 4. McGraw-Hill New York.

Kelln, B. M., McKeon, P. O., Gontkof, L. M., and Hertel, J. (2008). Hand-held dynamometry: reliability of lower extremity muscle testing in healthy, physically active, young adults. *Journal of Sport Rehabilitation*, 17(2):160.

Kempen, G. I., Yardley, L., Van Haastregt, J. C., Zijlstra, G. R., Beyer, N., Hauer, K., and Todd, C. (2008). The short fes-i: a shortened version of the falls efficacy scale-international to assess fear of falling. *Age and ageing*, 37(1):45–50.

Kennedy, T. E. (1987). The prevention of falls in later life. *DMB. Spec. suppl. ser., Gerontology*.

Kenny, R., Rubenstein, L. Z., Tinetti, M. E., Brewer, K., Cameron, K. A., Capezuti, L., John, D. P., Lamb, S. E., Martin, F., Rockey, P. H., et al. (2011). Summary of the updated american geriatrics society/british geriatrics society clinical practice guideline for prevention of falls in older persons. *Journal of the American Geriatrics Society*, 59(1):148–157.

Kerrigan, D. C., Lee, L. W., Collins, J. J., Riley, P. O., and Lipsitz, L. A. (2001). Reduced hip extension during walking: healthy elderly and fallers versus young adults. *Archives of physical medicine and rehabilitation*, 82(1):26–30.

Khattar, V. and Hathiram, B. (2012). The clinical test for the sensory interaction of balance. *Int J Otorhinolaryngol Clin*, 4:41–45.

Kim, B.-J. and Robinson, C. J. (2005). Postural control and detection of slip/fall initiation in the elderly population. *Ergonomics*, 48(9):1065–1085.

Koepsell, T. D., Wolf, M. E., Buchner, D. M., Kukull, W. A., LaCroix, A. Z., Tencer, A. F., Frankenfeld, C. L., Tautvydas, M., and Larson, E. B. (2004). Footwear style and risk of falls in older adults. *Journal of the American Geriatrics Society*, 52(9):1495–1501.

Kristinsdottir, E. K., Nordell, E., Jarnlo, G.-B., Tjäder, A., Thorngren, K.-G., and Magnusson, M. (2001). Observation of vestibular asymmetry in a majority of patients over 50 years with fall-related wrist fractures. *Acta oto-laryngologica*, 121(4):481–485.

Kuhn, M. and Johnson, K. (2013). *Applied predictive modeling*. Springer.

Kulas, J. F. and Naugle, R. I. (2003). Indications for neuropsychological assessment. *Cleveland Clinic journal of medicine*, 70(9):785–792.

Lajoie, Y. and Gallagher, S. (2004). Predicting falls within the elderly community: comparison of postural sway, reaction time, the berg balance scale and the activities-specific balance confidence (abc) scale for comparing fallers and non-fallers. *Archives of gerontology and geriatrics*, 38(1):11–26.

Last, M., Maimon, O., and Minkov, E. (2002). Improving stability of decision trees. *International Journal of Pattern Recognition and Artificial Intelligence*, 16(02):145–159.

Lee, D. and Lishman, J. (1975). Visual proprioceptive control of stance. *Journal of human movement studies*.

Legters, K. (2002). Fear of falling. *Physical therapy*, 82(3):264–272.

Liaw, A. and Wiener, M. (2002). Classification and regression by randomforest. *R news*, 2(3):18–22.

Lindle, R., Metter, E., Lynch, N., Fleg, J., Fozard, J., Tobin, J., Roy, T., and Hurley, B. (1997). Age and gender comparisons of muscle strength in 654 women and men aged 20–93 yr. *Journal of Applied Physiology*, 83(5):1581–1587.

Liu, Y., Redmond, S. J., Narayanan, M. R., and Lovell, N. H. (2011). Classification between non-multiple fallers and multiple fallers using a triaxial accelerometry-based system. In *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pages 1499–1502. IEEE.

Lord, S. R. and Clark, R. D. (1996). Simple physiological and clinical tests for the accurate prediction of falling in older people. *Gerontology*, 42(4):199–203.

Lord, S. R. et al. (2003a). Vision, balance and falls in the elderly. *Geriatric Times*, 4(6):9–10.

Lord, S. R. and Fitzpatrick, R. C. (2001). Choice stepping reaction time a composite measure of falls risk in older people. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 56(10):M627–M632.

Lord, S. R., Menz, H. B., and Tiedemann, A. (2003b). A physiological profile approach to falls risk assessment and prevention. *Physical therapy*, 83(3):237–252.

Lord, S. R., Sherrington, C., Menz, H. B., and Close, J. C. (2007). *Falls in older people: risk factors and strategies for prevention*. Cambridge University Press.

Lord, S. R., Ward, J. A., Williams, P., and Anstey, K. J. (1993). An epidemiological study of falls in older community-dwelling women: the randwick falls and fractures study. *Australian journal of public health*, 17(3):240–245.

Mackintosh, S. F., Hill, K. D., Dodd, K. J., Goldie, P. A., and Culham, E. G. (2006). Balance score and a history of falls in hospital predict recurrent falls in the 6 months following stroke rehabilitation. *Archives of physical medicine and rehabilitation*, 87(12):1583–1589.

Madgwick, S. O. (2010). An efficient orientation filter for inertial and inertial/magnetic sensor arrays. *Report x-io and University of Bristol (UK)*.

Mahurin, R. K. and Pirozzolo, F. J. (1993). Application of hick's law of response speed in alzheimer and parkinson diseases. *Perceptual and motor skills*, 77(1):107–113.

Mancini, M., Horak, F., Carlson-Kuhta, P., and Chiari, L. (2011). Accelerometers provide a sensitive measure of postural abnormalities in untreated parkinson's disease. *Parkinsonism and Related Disorders*, 17(7):557–62.

Mancini, M., Salarian, A., Carlson-Kuhta, P., Zampieri, C., King, L., Chiari, L., Horak, F. B., et al. (2012). Isway: a sensitive, valid and reliable measure of postural control. *J Neuroeng Rehabil*, 9(59):59.

Marschollek, M., Nemitz, G., Gietzelt, M., Wolf, K., Meyer zu Schwabedissen, H., and Haux, R. (2009). Predicting in-patient falls in a geriatric clinic. *Zeitschrift für Gerontologie und Geriatrie*, 42(4):317–322.

Marschollek, M., Rehwald, A., Wolf, K., Gietzelt, M., Nemitz, G., Meyer Zu Schwabedissen, H., and Haux, R. (2011a). Sensor-based fall risk assessment-an expert'to go'. *Methods of information in medicine*, 50(5):420.

Marschollek, M., Rehwald, A., Wolf, K.-H., Gietzelt, M., Nemitz, G., zu Schwabedissen, H. M., and Schulze, M. (2011b). Sensors vs. experts-a performance comparison of sensor-based fall risk assessment vs. conventional assessment in a sample of geriatric patients. *BMC medical informatics and decision making*, 11(1):48.

Masud, T. and Morris, R. O. (2001). Epidemiology of falls. *Age and ageing*, 30(suppl 4):3–7.

Mathers, C., Fat, D. M., and Boerma, J. T. (2008). *The global burden of disease: 2004 update*. World Health Organization.

Menant, J. C., Steele, J. R., Menz, H. B., Munro, B. J., and Lord, S. R. (2008). Optimizing footwear for older people at risk of falls.

Menz, H. B., Morris, M. E., and Lord, S. R. (2006). Footwear characteristics and risk of indoor and outdoor falls in older people. *Gerontology*, 52(3):174–180.

Mergner, T. and Rosemeier, T. (1998). Interaction of vestibular, somatosensory and visual signals for postural control and motion perception under terrestrial and microgravity conditions—a conceptual model. *Brain Research Reviews*, 28(1):118–135.

Moreland, J. D., Richardson, J. A., Goldsmith, C. H., and Clase, C. M. (2004). Muscle weakness and falls in older adults: a systematic review and meta-analysis. *Journal of the American Geriatrics Society*, 52(7):1121–1129.

Moylan, K. C. and Binder, E. F. (2007). Falls in older adults: risk assessment, management and prevention. *The American journal of medicine*, 120(6):493–e1.

Muir, S. W., Berg, K., Chesworth, B., and Speechley, M. (2008). Use of the berg balance scale for predicting multiple falls in community-dwelling elderly people: a prospective study. *Physical therapy*, 88(4):449–459.

Muir, S. W., Gopaul, K., and Odasso, M. M. M. (2012). The role of cognitive impairment in fall risk among older adults: a systematic review and meta-analysis. *Age and ageing*, 41(3):299–308.

Myers, A. M., Fletcher, P. C., Myers, A. H., and Sherk, W. (1998). Discriminative and evaluative properties of the activities-specific balance confidence (abc) scale. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 53(4):M287–M294.

Narayanan, M. R., Scalzi, M. E., Redmond, S. J., Lord, S. R., Celler, B. G., and Lovell, N. H. (2008). A wearable triaxial accelerometry system for longitudinal assessment of falls risk. In *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, pages 2840–2843. IEEE.

Newton, R. A. (2001). Validity of the multi-directional reach test a practical measure for limits of stability in older adults. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 56(4):M248–M252.

Oliver, D., Daly, F., Martin, F. C., and McMurdo, M. E. (2004). Risk factors and risk assessment tools for falls in hospital in-patients: a systematic review. *Age and ageing*, 33(2):122–130.

O'Sullivan, M., Blake, C., Cunningham, C., Boyle, G., and Finucane, C. (2009). Correlation of accelerometry with clinical balance tests in older fallers and non-fallers. *Age and ageing*, 38(3):308–313.

P. Di Fabio, Alongkot Emasithi, J. F. G. S. P. R. (2001). Suppression of the vertical vestibulo-ocular reflex in older persons at risk of falling. *Acta oto-laryngologica*, 121(6):707–714.

Parkkari, J., Kannus, P., Palvanen, M., Natri, A., Vainio, J., Aho, H., Vuori, I., and Järvinen, M. (1999). Majority of hip fractures occur as a result of a fall and impact on the greater trochanter of the femur: a prospective controlled hip fracture study with 206 consecutive patients. *Calcified Tissue International*, 65(3):183–187.

Perry, M. C., Carville, S. F., Smith, I. C. H., Rutherford, O. M., and Newham, D. J. (2007). Strength, power output and symmetry of leg muscles: effect of age and history of falling. *European journal of applied physiology*, 100(5):553–561.

Peters, P. G., Herbenick, M., Anloague, P., Markert, R., and Rubino 3rd, L. (2011). Knee range of motion: reliability and agreement of 3 measurement methods. *American journal of orthopedics (Belle Mead, NJ)*, 40(12):E249–52.

Piirtola, M. and Era, P. (2006). Force platform measurements as predictors of falls among older people–a review. *Gerontology*, 52(1):1–16.

Pijnappels, M., Delbaere, K., Sturnieks, D. L., and Lord, S. R. (2010). The association between choice stepping reaction time and falls in older adults—a path analysis model. *Age and ageing*, 39(1):99–104.

Pluijm, S. M., Smit, J. H., Tromp, E., Stel, V., Deeg, D. J., Bouter, L., and Lips, P. (2006). A risk profile for identifying community-dwelling elderly with a high risk of recurrent falling: results of a 3-year prospective study. *Osteoporosis International*, 17(3):417–425.

Podsiadlo, D. and Richardson, S. (1991). The timed" up & go": a test of basic functional mobility for frail elderly persons. *Journal of the American geriatrics Society*, 39(2):142–148.

Pollock, A. S., Durward, B. R., Rowe, P. J., and Paul, J. P. (2000). What is balance? *Clinical rehabilitation*, 14(4):402–406.

Powell, L. E. and Myers, A. M. (1995). The activities-specific balance confidence (abc) scale. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 50(1):M28–M34.

Qiu, H. and Xiong, S. (2015). Center-of-pressure based postural sway measures: Reliability and ability to distinguish between age, fear of falling and fall history. *International Journal of Industrial Ergonomics*, 47:37–44.

Roth, E. (1964). Die geschwindigkeit der verarbeitung von information und ihr zusammenhang mit intelligenz. *Zeitschrift fÃ1/4r Experimentelle und Angewandte Psychologie*.

Rubenstein, L. Z. (2006). Falls in older people: epidemiology, risk factors and strategies for prevention. *Age and ageing*, 35(suppl 2):ii37–ii41.

Ruggiero, C., Mariani, T., Gugliotta, R., Gasperini, B., Patacchini, F., Nguyen, H. N., Zampi, E., Serra, R., Dell'Aquila, G., Cirinei, E., et al. (2009). Validation of the italian version of the falls efficacy scale international (fes-i) and the short fes-i in community-dwelling older persons. *Archives of gerontology and geriatrics*, 49:211–219.

Salonen, L. and Kivelä, S.-L. (2012). Eye diseases and impaired vision as possible risk factors for recurrent falls in the aged: a systematic review. *Current gerontology and geriatrics research*, 2012.

Sandri, M. and Zuccolotto, P. (2008). A bias correction algorithm for the gini variable importance measure in classification trees. *Journal of Computational and Graphical Statistics*, 17(3).

Sartini, M., Cristina, M., Spagnolo, A., Cremonesi, P., Costaguta, C., Monacelli, F., Garau, J., and Odetti, P. (2010). The epidemiology of domestic injurious falls in a community dwelling elderly population: an outgrowing economic burden. *The European Journal of Public Health*, 20(5):604–606.

Schlicht, J., Camaione, D. N., and Owen, S. V. (2001). Effect of intense strength training on standing balance, walking speed, and sit-to-stand performance in older adults. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 56(5):M281–M286.

Schmidt, R. A. and Debû, B. (1993). *Apprentissage moteur et performance*. Vigot Paris.

Shaffer, S. W. and Harrison, A. L. (2007). Aging of the somatosensory system: a translational perspective. *Physical therapy*, 87(2):193–207.

Shumway-Cook, A., Baldwin, M., Polissar, N. L., and Gruber, W. (1997). Predicting the probability for falls in community-dwelling older adults. *Physical therapy*, 77(8):812–819.

Soechting, J. and Berthoz, A. (1979). Dynamic role of vision in the control of posture in man. *Experimental Brain Research*, 36(3):551–561.

Spink, M. J., Fotoohabadi, M. R., and Menz, H. B. (2010). Foot and ankle strength assessment using hand-held dynamometry: reliability and age-related differences. *Gerontology*, 56(6):525–532.

Stalenhoef, P., Diederiks, J., Knottnerus, J., Kester, A., and Crebolder, H. (2002). A risk model for the prediction of recurrent falls in community-dwelling elderly: a prospective cohort study. *Journal of clinical epidemiology*, 55(11):1088–1094.

Stel, V. S., Pluijm, S. M., Deeg, D. J., Smit, J. H., Bouter, L. M., and Lips, P. (2003a). A classification tree for predicting recurrent falling in community-dwelling older persons. *Journal of the American Geriatrics Society*, 51(10):1356–1364.

Stel, V. S., Smit, J. H., Pluijm, S. M., and Lips, P. (2003b). Balance and mobility performance as treatable risk factors for recurrent falling in older persons. *Journal of clinical epidemiology*, 56(7):659–668.

Sturnieks, D., St George, R., and Lord, S. (2008). Balance disorders in the elderly. *Neurophysiologie Clinique/Clinical Neurophysiology*, 38(6):467–478.

Swanenburg, J., de Bruin, E. D., Uebelhart, D., and Mulder, T. (2010). Falls prediction in elderly people: a 1-year prospective study. *Gait & posture*, 31(3):317–321.

Taylor, J. A., Parmelee, P., Brown, H., and Ouslander, J. (2005). *The falls management program: A quality improvement initiative for nursing facilities*. Center for Health in Aging and the Emory University, Division of Geriatric Medicine and Gerontology, Department of Medicine.

Tencer, A. F., Koepsell, T. D., Wolf, M. E., Frankenfeld, C. L., Buchner, D. M., Kukull, W. A., LaCroix, A. Z., Larson, E. B., and Tautvydas, M. (2004). Biomechanical properties of shoes and risk of falls in older adults. *Journal of the american geriatrics society*, 52(11):1840–1846.

Thigpen, M. T., Light, K. E., Creel, G. L., and Flynn, S. M. (2000). Turning difficulty characteristics of adults aged 65 years or older. *Physical Therapy*, 80(12):1174–1187.

Thorbahn, L. D. B. and Newton, R. A. (1996). Use of the berg balance test to predict falls in elderly persons. *Physical therapy*, 76(6):576–583.

Tinetti, M., Baker, D., Garrett, P., Gottschalk, M., Koch, M., and Horwitz, R. (1993). Yale ficsit: risk factor abatement strategy for fall prevention. *Journal of the American Geriatrics Society*, 41(3):315–320.

Tinetti, M. E. and Kumar, C. (2010). The patient who falls:"it's always a trade-off". *Jama*, 303(3):258–266.

Tinetti, M. E., Richman, D., and Powell, L. (1990). Falls efficacy as a measure of fear of falling. *Journal of gerontology*, 45(6):P239–P243.

Tinetti, M. E., Williams, T. F., and Mayewski, R. (1986). Fall risk index for elderly patients based on number of chronic disabilities. *The American journal of medicine*, 80(3):429–434.

Tromp, A., Pluijm, S., Smit, J., Deeg, D., Bouter, L., and Lips, P. (2001). Fall-risk screening test: a prospective study on predictors for falls in community-dwelling elderly. *Journal of clinical epidemiology*, 54(8):837–844.

VA National Center for Patient Safety (2015). Fall toolkit.

Vellas, B. J., Wayne, S. J., Romero, L. J., Baumgartner, R. N., and Garry, P. J. (1997). Fear of falling and restriction of mobility in elderly fallers. *Age and ageing*, 26(3):189–193.

Verghese, J., Holtzer, R., Lipton, R. B., and Wang, C. (2009). Quantitative gait markers and incident fall risk in older adults. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 64(8):896–901.

Visser, J. E., Carpenter, M. G., van der Kooij, H., and Bloem, B. R. (2008). The clinical utility of posturography. *Clinical Neurophysiology*, 119(11):2424–2436.

Wang, Y.-C., Lin, F.-G., Yu, C.-P., Tzeng, Y.-M., Liang, C.-K., Chang, Y.-W., Chou, C.-C., Chien, W.-C., and Kao, S. (2012). Depression as a predictor of falls amongst institutionalized elders. *Aging & mental health*, 16(6):763–770.

Watson, M. A. and Black, F. O. (2008). The human balance system–a complex coordination of central and peripheral systems. *VEDA Publication: No. S-7*.

Weiss, A., Herman, T., Plotnik, M., Brozgol, M., Giladi, N., and Hausdorff, J. (2011). An instrumented timed up and go: the added value of an accelerometer for identifying fall risk in idiopathic fallers. *Physiological measurement*, 32(12):2003.

Whitney, S. L. and Wrisley, D. M. (2004). The influence of footwear on timed balance scores of the modified clinical test of sensory interaction and balance. *Archives of physical medicine and rehabilitation*, 85(3):439–443.

Winter, D. A. (1995). Human balance and posture control during standing and walking. *Gait & posture*, 3(4):193–214.

Woolley, S. M., Czaja, S. J., and Drury, C. G. (1997). An assessment of falls in elderly men and women. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 52(2):M80–M87.

Yamashita, T., Noe, D. A., and Bailer, A. J. (2012). Risk factors of falls in community-dwelling older adults: Logistic regression tree analysis. *The Gerontologist*, page gns043.

Yardley, L., Beyer, N., Hauer, K., Kempen, G., Piot-Ziegler, C., and Todd, C. (2005). Development and initial validation of the falls efficacy scale-international (fes-i). *Age and ageing*, 34(6):614–619.

Yu, W.-Y., Hwang, H.-F., Hu, M.-H., Chen, C.-Y., and Lin, M.-R. (2013). Effects of fall injury type and discharge placement on mortality, hospitalization, falls, and adl changes among older people in taiwan. *Accident Analysis & Prevention*, 50:887–894.

Zijlstra, W. and Hof, A. L. (2003). Assessment of spatio-temporal gait parameters from trunk accelerations during human walking. *Gait & posture*, 18(2):1–10.