FALL REDUCTION ALGORITHM BASED ON ABNORMAL GAITS DETECTION

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By

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ABSTRACT

Falls lead to injuries and fatality. Studies have been carried out to create systems to detect falls; however, fall detection is sometimes too late to prevent injuries or fatalities. Studies on fall prediction have also revealed that fall prediction is hard as there are many factors that can lead to falls. Abnormal gait is one of the common factors for falls, but the linkage between human trunk acceleration in normal gait and abnormal gait with falls is still unclear. The aims of this study are to investigate the trunk acceleration in normal and abnormal gaits and exploit this relationship to introduce threshold-based fall reduction algorithms.

Firstly, a tri-axial accelerometer was used in this research to capture 3-dimensional trunk acceleration for 144 healthy subjects. Trunk acceleration data in simulated normal and abnormal gaits were collected and analysed using the statistical analysis software IBM SPSS. In this research, quantitative analysis results have identified a significant difference between trunk acceleration in normal and abnormal gaits. Particularly, trunk acceleration of abnormal gaits in medio-lateral, anterior-posterior and vertical directions are 257%, 376% and 217% larger than those of a normal gait respectively.

Based on simulated normal and abnormal gaits statistical analysis results, a novel universal fall reduction algorithm that consists of universal abnormal gait detection threshold and universal near fall detection threshold was proposed in this research. To evaluate the effectiveness of the proposed

universal fall reduction algorithm, an Android-based fall reduction mobile apps was developed using a smartphone that is equipped with an accelerometer. The detection rate for abnormal gait and near fall gait was 98% and 90% respectively.

To improve the accuracy of universal fall reduction algorithm, an individual fall reduction algorithm that consists of individual abnormal gait detection threshold and individual near fall detection threshold was proposed in this research. The individual fall reduction algorithm was inspired from the observation noticed in the simulated normal gait and abnormal gait experiments where the gait cycle duration and the trunk acceleration amplitude for each individual test subject were similar, but different from other test subjects. Experiment results showed that the self-learning fall reduction algorithm can detect 100% of both the abnormal gait and near fall gait. Thus, the self-learning fall reduction mobile apps can be developed to provide an alert message to the caregiver and to remind the user automatically whenever the thresholds are exceeded. This application is particularly important to older adults to reduce falls and help to prolong their lives.

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APPROVAL SHEET

This thesis entitled "**FALL REDUCTION ALGORITHM BASED ON ABNORMAL GAITS DETECTION**" was prepared by CHUAH YEA DAT and submitted as partial fulfilment of the requirements for the degree of Doctor of Philosophy in Engineering at Universiti Tunku Abdul Rahman.

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DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

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LIST OF ABBREVATIONS

AP	Anterior-posterior axis
CI	Confidence Interval
DIN	Deutsches Institut für Normung (German Institute for Standardization)
ML	Medio lateral axis
USB	Universal Serial Bus
VT	Vertical axis

CHAPTER 1

INTRODUCTION

1.1 Background

Second leading cause of accidents that may result in deaths is fall (World Health Organization, 2017). As such, falls related research has attracted much attention worldwide. Research outcomes have shown that the consequences of falls are injury, hospitalisation, death, the increased of healthcare cost and the reduced confidence of the elderly to live alone. (Alexander, 1992; CDC, 2017; Department of Health, Social Services and Public Safety, 2016; Najafi et al., 2002; Tinetti et al., 1998). According to Sterling (2001), seniors who were injured as a result of falls such as hip fractures would stay in a hospital for a year or more due to functional impairments.

In Malaysia, the population aged 65 years and over has reached 5.9 per cent (i.e., 1.8 million persons) (Department of Statistics Malaysia, 2016) and World Health Organization (2017) has reported adults who are older than 65 years old have suffered the greatest number of fatal falls. Due to the high risk of fall for ageing people and the increasing population of seniors, falls have become one of the major concerns worldwide. Therefore, it is important to seek possibilities of reducing or preventing falls.

Falls detection related research has been carried out worldwide. Unfortunately, falls detection is too late to help the people who have fallen. On the other hand, fall prediction cannot achieve 100% accuracy due to many factors that can result in falls (Lim et al., 2011; Marschollek et al., 2016; Weiss et al., 2010). Therefore, it is necessary to find a practical solution to reduce the numbers of falls during walking that may result in injury, fatality or hospitalisation.

The human gaits are classified into two categories which are steady gait and unsteady gait. Steady gait and unsteady gait are also defined as normal gait and abnormal gait respectively. Abnormal gait is one of the factors for falls (Rubenstein, 2006), but the association between trunk acceleration in normal gait and abnormal gait with falls is still unclear. It is interesting if experiments can be carried out to study and simulate the relationship between trunk acceleration in normal gait and abnormal gait with falls. Subsequently, a fall reduction algorithm, that is, a way to detect or predict fall, can be developed if the relationship between trunk acceleration in normal gait and abnormal gait with falls can be identified.

1.2 Aims and objectives

The aims of this research is to study the relationship between human trunk accelerations in normal gait and abnormal gait with fall and to create a fall reduction algorithm based on the identified relationship between trunk acceleration in normal and abnormal gaits with falls. More precisely, to achieve the aforementioned aims, the objectives of this research project are listed as follows.

1. To design experimental methods to capture trunk accelerations in normal gait and abnormal gait.
2. To identify the correlation between human trunk acceleration and human locomotion in terms of normal gait and abnormal gait.
3. To propose a method to classify gaits into normal and abnormal based on trunk acceleration.
4. To design fall reduction algorithms based on the trunk acceleration.

1.3 Research contributions

In short, new methods to conduct human locomotion experiments in terms of the normal and abnormal gaits are introduced in this research. The trunk acceleration data for both normal gait and abnormal gait is analysed by using statistical methods. The analysis is then used to propose fall reduction algorithms. Lastly, experiments are carried out to evaluate the reliability of the proposed fall reduction algorithms. In a nutshell, the contribution of this research is twofold and is listed as follows:

1. The outcome of this research shows that there is an association between trunk acceleration and human gait. Trunk acceleration in normal gait demonstrates a consistent periodical gait cycle pattern and peak-to-peak amplitude while trunk acceleration in abnormal gait shows random gait

cycle pattern and different peak-to-peak amplitude. Trunk acceleration in abnormal gait is significantly greater than that of normal gait. As such, trunk acceleration in gaits can be exploited to classify normal and abnormal gaits.

2. The successful classification of abnormal and normal gaits lead to the proposal of two fall reduction algorithms, namely universal fall reduction algorithm and individual fall reduction algorithm. Universal fall reduction algorithm consists of generic threshold obtained from the simulated normal and abnormal gait experiments. Meanwhile, individual fall reduction algorithm consists of unique personal threshold. Experimental results showed that the detection rate for universal fall reduction algorithm and individual fall reduction algorithm is 90% and 100% respectively.

Important finding includes the trunk acceleration in normal and abnormal gaits is different for every individual which implies that each individual has different lower extremity strength and sensory-motor condition. It is noteworthy to highlight that, this finding is consistent with the finding of Cordero et al. (2003). More precisely, Cordero et al. (2003) found that the ability to recover from abnormal gait is depend on the physical condition of an individual.

1.4 Structure of the thesis

The remainder of this thesis is structured as follows. Chapter 2 first briefly describes the risk factors and consequences of falls. Different fall detection methods and fall prediction methods are then described in terms of the approaches used and the accuracy of the proposed methods. To understand the relationship between falls and human gaits, the study and background of human gaits are presented. Lastly, the shortage of existing fall related research that motivates this research project is highlighted.

Chapter 3 aims to study the trunk acceleration in normal gait and abnormal gait. To achieve this aim, trunk acceleration data of 144 test subjects are collected using the proposed experiments. The health condition, genders, ages, heights and weights of the test subjects are first described. Subsequently, experiment setup and procedure for the simulated trunk acceleration in normal gait and abnormal gait are elaborated with the help of the diagrams.

Chapter 4 consists of experimental results and discussion on the trunk acceleration in normal gait and abnormal gait. Experimental results include individual trunk acceleration waveform, the statistical analysis result of all test subjects, the comparison of the mean value of trunk acceleration between the elderly and young, male and female test subjects, visual observation outcomes of the test subjects and the recovery action taken by the test subjects when they experienced gait disorder. The results of the experiments are then explained based on Newton's Second Law of motion. Lastly, the correlation between forward trunk acceleration and trunk leaning angle during walking is discussed.

Chapter 5 proposes the methods to define universal abnormal gait detection threshold and universal near fall detection threshold by exploiting the findings of Chapter 4. These two thresholds are then used to develop a universal fall reduction algorithm. To evaluate the effectiveness of the developed universal fall reduction algorithm, the sensitivity or accuracy performance is measured. To further improve the universal fall reduction system, an individual threshold is proposed. Finally, the sensitivity or accuracy performance of developed individual fall reduction algorithm is evaluated to check its effectiveness.

Chapter 6 concludes the outcomes of the research. The findings of the study are summarised. Furthermore, the potential directions that can also be explored are recommended.

CHAPTER 2

LITERATURE REVIEW

2.1 Status quo of falls

2.1.1 Introduction

Falls represent a sudden uncontrollable descent that may result in injury or death. With an increasing rate of ageing population in the world (United Nation, 2017), elderly falls have became one of the major problems that need immediate attention. Therefore, many efforts have been carried out worldwide to identify the reasons of falls and the risks of falls.

2.1.2 Fall related research and the study outcomes

Loganathan et al. (2016) identified various views on falls, help-seeking behaviour and logistic difficulties to establish falls interventions among elderly. The finding of this study indicated that the ethnic and cultural differences among older persons must be considered in tackling issues about falls prevention. Besides, the lacking of structured fall prevention guidelines and insufficient training on fall management led to the inability of healthcare professional to address fall prevention among elderly adequately (Loganathan et al., 2015). In addition, Pohl et al. (2015) investigated the risks of fall and safety measures taken to prevent falls among the elderly. Pohl et al.

commented that the awareness on the risk of falls should be promoted to elderly. Tan et al. (2014) took a further step to propose the methods in evaluating individually-tailored multi-faceted interventions on falls, but the outcome of their study was not conclusive. On the other hand, Kim et al. (2013) found that, in Malaysia, the annual prevalence of falls in rural dwellers older than 60 years was 27% of which 67% involved home falls.

Falls are the most frequent cause of injury at home for elderly people (Lim et al., 2013). Stevens et al. (2012) conducted a survey to identify the willingness of women and men in seeking medical assistance and information that are related to falls from health care service providers. The results indicated that men are more reluctant to seek medical assistance and information related to falls.

To reduce the chances of falls among elderly people who live in a community, Gillespie et al. (2012) conducted an assessment to identify the effectiveness of existing interventions. The assessment outcomes concluded that the risk and the rate of falls will be reduced by carrying out group- and home-based exercise programs and home safety interventions. For an example, practising Tai Chi can improve balancing and thus can reduce the risk of falls. Meanwhile, multi-factorial assessment and response program can reduce the rate of falls (Gillespie et al., 2012).

2.1.3 Risk factors of falls

Ageing, impaired physical function, impaired cognition, chronic diseases and environmental hazards represent the risk factors of falls (Yasumura et. al, 1996). Falls in young and middle-aged adults are often results of sports and vigorous activity, side-effect of medication, lower levels of physical activity and physiological changes that alter postural stability (Talbot et. al, 2005). On the other hand, Rubenstein (2006) reported that diseases and physiological functions degradation are the main reasons of falls among elderly. In addition, falls of the elderly are associated with one or more identifiable risk factors such as unstable gait and medications that degrade physiological functions.

According to David et al. (1990), the balance control of ageing people degenerates and thus causes the falls in elderly. Similarly, Criak (1989) also concluded that elderly falls are due to balance disorder and inability to recover from balance disorder. There are several factors that may affect balance control. Puggaard et al. (2000) confirmed that the condition of human visual and cardiovascular systems will affect balance control. Besides, Kerrigan et al. (2001) and Burnfield et al. (2000) identified that the condition of neuro muscular system and human skeleton will affect body balancing control. In addition, cognition ability, the use of medication, and environmental factors will also impair balance control (Koski et al. 1998; Tinetti et al. 1995). According to Hausdorff et al. (1997) and Wolfson et al. (1990), neuromuscular pathologies is the leading cause of falls and elderly people with a history of falls suffer from abnormal gait compared with seniors without any history of falls. Salzman (2010) reported that gait and balance disorders are common in elderly and the causes of falls are related to the increased morbidity, reduced level of body physical function and illness such as arthritis and orthostatic hypotension. The factors of falls are summarised in Table 2.1.

Table 2.1: Factors of falls

Factors of fall	**References**
Degradation of physiological functions	(Burnfield et al., 2000; Craik, 1989; David et al., 1990; Hausdorff et al., 1997; Kerrigan et al., 2001; Puggaard et al., 2000; Rubenstein, 2006; Talbot et al., 2005; Wolfson et al., 1990; Yasumura, et al., 1996)
Diseases	(Talbot et al., 2005; Yasumura, et al., 1996)
Environmental hazards	(Koski et al., 1998; Tinetti et al., 1995; Yasumura, et al., 1996)
Medication	(Koski et al., 1998; Rubenstein, 2006; Talbot et al., 2005; Tinetti et al., 1995)

2.1.4 Falls induced risks

According to Alexander et al. (1992), falls that have caused injury and require medical attention can be as high as 30%. Fall injury is the fifth leading cause of death among elderly people (Kannus et al., 1999). Independent of the finding reported by Kannus et al. (1999), similar finding had been reported by Ambrose et al. (2013) and Deandrea (2010) where the major cause of injury and death among elderly people is falls.

In Finland, Kannus et al. (1999) carried out 30 years survey to identify the numbers of deaths that resulted from falls on elderly. The survey outcome revealed that the numbers of deaths that resulted from falls on elderly in Finland has increased. In United States, there were 2.8 million older people treated in emergency departments and over 800,000 patients hospitalised in a year due to falls (Centers for Disease Control and Prevention, 2017). Meanwhile, in United Kingdom, falls account for 71% of total fatal accidents to people aged 65 and over with the number continuing to increase (Department of Health, Social Services and Public Safety, 2016).

In Malaysia, Kim et al. (2013) carried out a 10 years study on elderly people with falls that result in admittance to hospital emergency department. The results showed that 70% of falls occurred indoors. Research has shown that more than 33% of older people fall at least once in a year (Hausdorff et al., 2001; Hornbrook et al., 1994). 32% of the elderly aged more than 75 years, have a fall at least once in a year, and 24% of the falls caused serious injury (Najafi et al., 2002; Tinetti et al., 1998).

Elderly falls are considered as a major public health problem that will affect the health condition of elderly and increase public healthcare costs (Najafi et al., 2002). Falls demotivate and decrease the self-confidence of older adults to live alone (Hwang et al., 2004). Table 2.2 summarise the possible results of falls. As falls will produce many negative impacts to the individual and to the society, it is necessary to seek ways to reduce or prevent falls.

Table 2.2: Falls induced risks

Falls induced risks	**References**
Injuries	(Alexander et al.,1992; Deandrea et al., 2010; Hausdorff et al., 2013; Lim et al., 2013; Najafi et al., 2002; Tinetti et al., 1998)
Death	(Deandrea et al., 2010; Department of Health, Social Services and Public Safety, 2016; Hausdorff et al., 2013; Kannus et al., 1999)
Hospitalisation	(Centres for Disease Control and Prevention, 2016; Kim et al., 2013)
Increase public and personal medical cost	(Najafi et al., 2002)
Reduce the self-confidence of elderly	(Hwang et al., 2004)

2.2 Falls detection

2.2.1 Introduction

Falls detector is a system that is able to detect falls and alert the user or the caregivers. Fall detector or fall detection system is designed to reduce the risks of falls and to save the medical costs that are associated with falls. The advancement in sensor and computer technology has made it possible to develop a reliable fall detection system. As of today, one of the most popular assistive gadgets for elderly is the fall detector.

2.2.2 Fall detection system and its performances

Various efforts have been carried out to detect falls by applying various technologies. Table 2.3 summarises the recent research works that were carried out in relation to the use of various sensing technologies for fall detection systems.

Chuah et al. (2016) used ultrasound sensor and infrared sensor to detect falls of the bathroom users of different heights. Omar et al. (2014) evaluated the sensitivity of a fall detector that is able to detect falls and identify the cause of falls. The evaluation outcomes showed that the sensors located at left and right of the ankle and sternum can achieve 83% accuracy. On the other hand, by monitoring improper body weight shifting during sitting, turning and reaching, slips and trips, the designed falls detector can achieve 89% accuracy in detecting falls.

Mubashir et al. (2013) carried out an in-depth survey of different fall detection systems and their underlying algorithms. The fall detection systems can be classified as wearable device based, ambience device based or vision based as illustrated in Figure 2.1. The review showed that there is room for improvement to increase the consistency of sensor-based fall detectors. Besides, further research and development should be carried out to automate the system without much intervention. Existing vision-based fall detectors are still lacking of flexibility as most of the systems are designed based on specific application.

There is a need to produce a reliable, robust yet generic vision based fall detector. It was also found that modern ambience based and sensor based falls detection systems were not properly evaluated in terms of the reliability and the accuracy of the systems. The video recorded by the camera or the data captured by the sensor in the falls detection system may also lead to the privacy issues of the users.

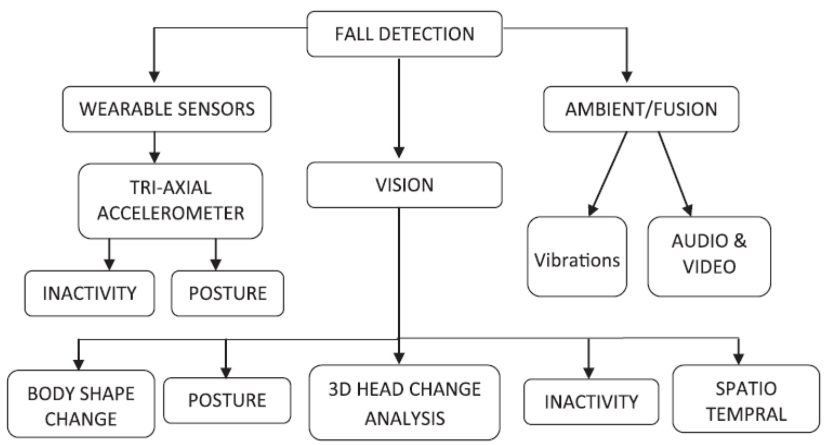


Figure 2.1: Classification of fall detection methods (Mubashir et al., 2013)

Igual et al. (2013) carried out an extensive literature review of fall detectors to identify challenges, limitations, and future trends in the area of fall detection. The study indicated that vision-based systems have received increased attention. It was also found that, fall detection system had been developed and integrated into smartphones. However, limited research had been done to evaluate the smartphone based fall detection system from the system design point of view. Thus, there is an urgent need to perform evaluation on smartphone based fall detection system against the criteria of user experience and expectation verification, power consumption, limitation of existing sensor technology, the sensitivity of the system, data privacy and security, real-time data logging and data transmission.

Liu et al. (2010) designed an algorithm for a fall detection system that can achieve the sensitivity of 84.44% in detecting horizontal position and falls. Zhuang et al. (2009) utilised an audio signal obtained from a microphone to detect falls at home by filtering the noise using machine a learning approach. By running the experiment based on a dataset of human falls, the results showed that the method can successfully improve fall classification from 59% to 67%. This approach can also effectively identify the falls even though audio segment boundaries of an audio signal are unknown.

Lan et al. (2009) developed an automatic fall detection system for the elderly who used canes as an assistive device to overcome balance disorder and leg weakness problems. This fall detection system was integrated with a specially designed stick to detect falls automatically. The fall detection system consists of sensors, such as motion, force, pressure, and gyroscope with data acquisition unit and communication unit. Experiments were conducted to evaluate the performance of the fall detection system. The results indicated that the algorithm was able to detect nearly 100% of falling.

Dobashi et al. (2008) created a fall detection system using ultrasound sensors installed on the ceiling of the bathroom to detect slip and fall accidents in a bathroom quickly. The system used ultrasound sensors to measure the distance between the sensor and the subject. Falls will be identified when the distance between the sensor and the subject changes suddenly. The experimental result indicated that the sensitivity of the fall detection system was 100%.

Bourke and Lyons (2008) used a biaxial gyroscope sensor to create a fall detection system. A gyroscope sensor was used to measure pitch and roll angular velocities at trunk. Matlab was used to carry out data analysis to identify the trunk angular accelerations, trunk angular velocities and changes in trunk angle. The system was also able to classify the activities of daily living by using three different types of thresholds. The evaluation results showed the system is able to differentiate falls from other daily-life activities with 100% accuracy.

Bourke et al. (2007) mounted tri-axial accelerometer on the trunk and captured acceleration of different types of daily-life activities and falls. The data collected in the experiment was analysed using Matlab to identify the peak accelerations for eight different types of falls. In the experiment, a threshold was defined based on the fall data derived from the resultant magnitude acceleration signal from accelerometer. The trunk and thigh thresholds were also used to determine the number of activities of daily living. The results showed that 67–100% of activities of daily living were correctly identified. However, result of distinguishing activities of daily-life and falls was not presented.

Yu (2008) conducted a survey on the existing methods to detect falls among elderly and patient. Different approaches and methods to detect falls for elderly and patients can be generalised using a general framework as shown in Figure 2.2. The fall detection system consists of sensors and/or camera, data acquisition system, data processing and feature extraction, fall detection algorithm and fall alert message to the caregivers through a wire or wireless communication.

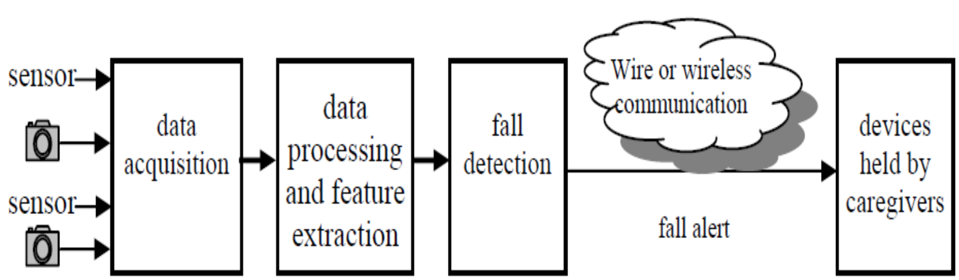


Figure 2.2: General framework of fall detection system (Yu, 2008)

Table 2.3: Summary of components used in fall detection systems and their sensitivities or outcomes achieved

Components used	Outcomes/sensitivity	References
Ultrasound sensors, infrared sensor	100% (able to detect falls of the bathroom users of different heights)	Chuah et al. (2016)
Tri-axial accelerometers and cameras	83% (sensors at left ankle, right ankle and sternum) and 89% (classifying falls due to slips, trips, and incorrect shift of body weight)	Omar et al. (2014)
Tri-axial accelerometers, microphone and cameras	There is still space to improve the sensor sensitivity.	Mubashir et al. (2013)
Web camera	The system has the accuracy of 84.44% on fall detection and horizontal position detection.	Liu et al. (2010)
Single far-field microphone	This method improved fall classification to 67% from 59%.	Zhuang et al. (2009)
Motion sensor, a force sensor, pressure sensor and gyroscope	The algorithm was able to detect near 100% of falling in the experiments.	Lan et al. (2009)
Ultrasound sensors	The accuracy of detecting the bather's fall was 100%.	Dobashi et al. (2008)
Bi-axial gyroscope sensor	100% distinguished falls from activities of daily living.	Bourke and Lyons (2008)
Tri-axial accelerometer sensors	67- 100% of activities of daily living tasks were correctly classified.	Bourke et al. (2007)
Omni camera	The detection rates with and without personal information were 79.8% and 68%.	Miaou et al. (2006)

Miaou et al. (2006) used images of Omni camera and personal information to design a fall detection system. The functions of the Omni camera were able to captured 360º scenes and eliminate blind viewing zone. The fall detection system required the user to key in information such as medical history, weight and height into the system. The experimental results showed that the sensitivity of the fall detections using Omni camera and user information was higher (i.e., 79.8%) as compared with the system without user information (i.e., 68%). Table 2.3 summarises the components used in different fall detection systems and their respective outcomes or sensitivities achieved.

2.3 Falls prediction

2.3.1 Introduction

Falls prediction is a system that is able to predict falls and alerts the user or the caregivers. Fall prediction system is designed to reduce the risks of falls. Different methods had been attempted to identify a reliable fall prediction system.

2.3.2 Fall prevention or prediction related research

Marschollek et al. (2017) carried out fall detection and fall prediction experiments by using vision sensor and accelerometers. Palumbo et al. (2016) evaluated the performance of Fall Risk Assessment Tool for Community-Dwelling Older People (FRAT-up) in four European Cohorts. They have concluded that FRAT-up is a valid approach to estimate risk of falls for elderly. However, further studies should be performed to identify the reasons for the observed heterogeneity across studies and to refine a tool that shows homogeneity.

Razmara et al. (2016) applied multi-layer neural network with back-propagation learning algorithm based on a physiological profile approach to predict the fall risk of elders. The accuracy for fall prediction among the physiological factors such as bodily action was 90 percent and the accuracy for fall prediction among the public factors such as age and health condition was 87.5 percent. The result concluded that, fall can be predicted based on a physiological profile such as vision abilities and muscle strength.

Van Schooten et al. (2015) applied daily-life accelerometry to investigate the relationship between retrospective and prospective falls on elderly with identified risks factor. In this study, total number of daily activity and gait quality of the elderly were identified and confirmed. In addition, the information related to grip strength, the risk factors on fall and trail making test were gathered from the elderly. The study outcomes have showed that, daily-life accelerometry was able to identify the potential risk of falls among the elderly and precisely forecast the risk of falls within six months. Weiss et al. (2010) suggested that tri-axial accelerometers can be applied to classify near falls condition from other gait patterns observed in the laboratory. However, no further fall prediction method had been proposed based on tri-axial accelerometers.

Table 2.4: Summary of fall prediction systems

Methods/ sensors used to predict falls	**Outcomes**	**Approaches**
Vision sensor and accelerometers	No result was reported.	Marschollek et al. (2017) carried out fall prediction experiment.
Data-based analysis without using any sensor.	Fall Risk Assessment Tool can be used to estimate risk of falls of elderly.	Palumbo et al. (2016) evaluated the performance of Fall Risk Assessment Tool for Community-Dwelling Older People.
Neural network with back-propagation learning algorithm using sensor.	The experimental results showed an accuracy of 90 percent and 87.5 percent for fall prediction among the psychological and public factors. The accuracy was improved to 91 percent by combining these two datasets.	Razmara et al. (2016) applied multilayer neural network with a back-propagation learning algorithm to predict elders fall risk.
Accelerometer	Daily-life accelerometry was able to identify the potential risk of falls among the elderly and precisely forecast the risk of falls within six months	Van Schooten et al. (2015) conducted a study by using daily-life accelerometry on elderly.
Tri-axial accelerometers.	No further fall prediction methods or algorithms were proposed.	Weiss et al. (2010) suggested that tri-axial accelerometers may be used to distinguish near falls from other gait patterns.
Pressure sensors.	No experiment was carried out.	Lim et al. (2011) suggested a fainted fall prediction system by monitoring the blood pressure.

Lim et al. (2011) proposed to design a fall prediction system by monitoring the blood pressure fluctuation in predicting a faint fall. However, no experimental result had been reported. From the above studies, it has been found that only a few fall prediction methods have been proposed, but with little evidence of an effective fall prediction system. The literature review on the fall prediction system is summarised in Table 2.4.

2.4 Human gaits

2.4.1 Introduction

In order to understand the proposed approach based on human gait, biped locomotion of humans must properly be understood. Therefore, a background to gait-related research is provided here.

2.4.2 Human locomotion

Sauders et al. (1959) explained human locomotion as a bipedal cyclical activity to move the human body from one place to another place by using human lower limbs. Human locomotion can be classified as walking and running. During walking, either one foot or both feet has contact with the ground at all times. During running, one foot is in contact with the ground which is then followed by both feet simultaneously off the ground (Saibene et al., 2003). According to Inman et al. (1981), human gait appears to be a learned skill. Toddlers never attempt to stand or walk without training. They need help from caregivers to establish the static and dynamic balance ability to walk upright. The body's centre of gravity is continuously maintained by the base support of both feet during the standing phase to allow an upright standing position. Double support stance in standing phase prevents imbalance, retains the postures and prevents stance leg from collapsing (Winter, 1980).

2.4.3 Gaits of healthy adult

The gait of a healthy adult without any gait disturbance can be categorised into four phases which are standing phase, initiation phase, steady-state phase and termination phase as illustrated in Figure 2.3.

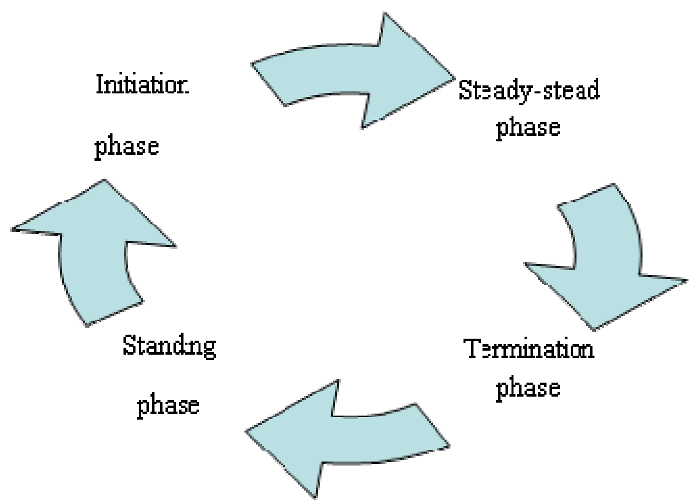


Figure 2.3: Phases in human gait

During initiation phase of gait, one limb is pushing at a great force while the other limb is acquiring the full weight of body (Winter et al., 1990). The body's centre of gravity is disrupted and becomes unstable where it falls forward and outward of the positioning foot (Mann et al. 1979). In steady-state phase, stride period consists of 80% single-support stance and 20% double-support stance. The weight-accepting foot first undergoes heel contact as the foot lowers to the ground at the beginning of the double-support stance before ending with the toe bearing most of the body weight. The body is at an unstable state at this moment. The double support stance is then re-established when both the limbs start to reduce its forward force and prepare for termination before reaching back to the standing phase (Winter et al., 1990). The termination of human gait is described as a progression from a steady-state motion to a standing still position as shown in Figure 2.4.

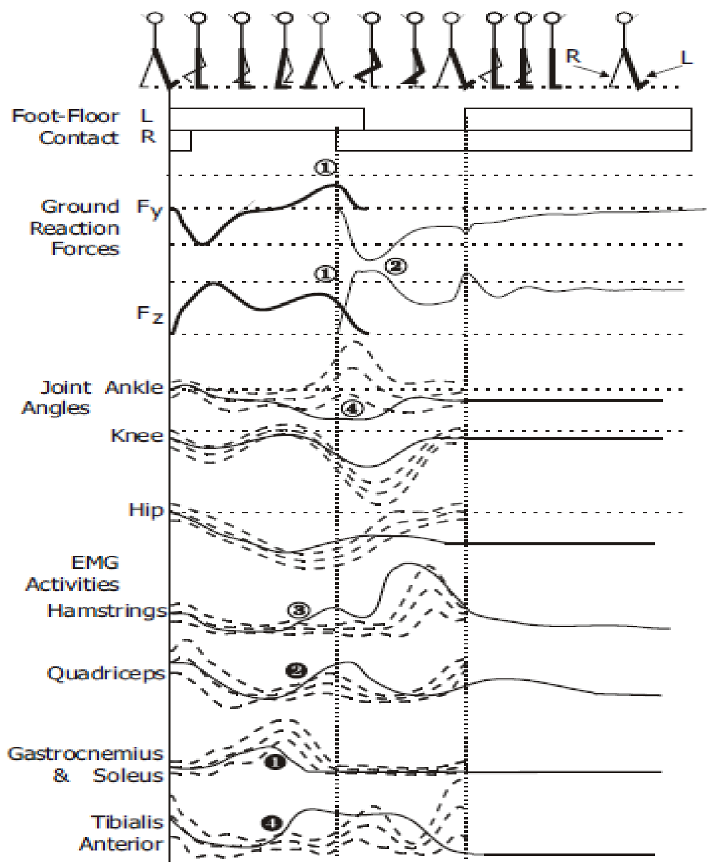


Figure 2.4: Events during Gait Termination (Vanitchatchavan, 2009)

Roger and John (1979) reported that stance phase is the period where the foot is on the ground and it occupies 60% of the gait cycle consisting of

20% double stance and 40% single stance. Investigations were performed in many studies to focus on the relationship between the variability of step kinematics and falls. Owings and Grabiner (2004) investigated the factor of age, walking velocity and handrail use on the step kinematics variability based on an instrumented treadmill. Their results indicated a consistent relationship between step width variability and age where step width variability had been related with falls in previous studies (Maki, 1997; Hausdorff et al., 2001).

2.4.4 The study of elderly gaits

Gait parameters are important in assessing elderly impairment in balance control, condition of sensory-motor functionality and the risk of fall among elderly. Elderly gaits demonstrated shorter and broader strides, reduced ankle movement and smaller swing-to-stance time ratio. As a result, this has caused the increase of the double support period in elderly gaits (Ferrandze et al., 1988; Hageman and Blanke, 1986; Winter et al., 1990; Kressig et al., 2004). In fact, there were many causes for the slow gait and shorter strides of the elderly. One of the main causes was weaker muscles in the lower limbs. Shorter strides were able to reduce the energy consumption during walking (Larish et al., 1988). Danion et al. (2003) investigated the stride length parameters and stride frequency in human gait. The investigation outcomes showed that, the stride frequency increases with stride length. Meanwhile, reduction in ankle and knee joints flexibility limited the stride length (Bertram, 2005). Except for unpredicted perturbation that resulted in balance disorder, a slower gait was able to help elderly in monitoring the ability of their balance control during walking and provide longer time for the elderly to respond to change of the environment such as floor condition (Spirduso, 1995). The chances of falls have increased as the dynamic balance control among elderly become increasingly difficult (Winter et al., 1990). Almarwani et al. (2016) examined the impact of challenging walking conditions in terms of gait speeds in younger and elderly people and discovered that slow gait was more challenging to the motor control of gait and more sensitive to age-related declines in gait.

2.4.5. The study of gaits as a mechanical system

The easiest and most common model used to describe human walking is the inverted pendulum model (Kuo, 2002; Winter et al., 1993). In this model, human walking is characterised by two variables: the centre of mass and the centre of pressure. The two variables are crucial in assessing energy expenditure and stability of human walking (Schepers et al., 2009).

Among the factors that will cause the change in the centre of gravity include body shape, age, gender, displacement of the body and neuro-musculoskeletal malfunctions. In addition, the amount of body fat and the reduction of soft tissue will also cause the change in the centre of gravity. Body movement that will cause the changes in alignment, stretching of the muscles and displacement of joints can shift the body centre of gravity (Schafer, 1987).

The centre of gravity of a body is continuously maintained by the base support of both feet during the standing phase to permit an upright standing position. The motion pattern of the upper part of the body is essential for reducing energy consumption (Cappozzo et al., 1978) and maintaining balance (Pozzo et al., 1990). Hanlon and Anderson (2006) and Hirasaki et al. (1996) discovered that, gait velocity will affect the kinematics of body segments. Lamonth et al. (2002) observed that, the increase of gait velocity will cause three phase component to emerge in the pelvic rotation, while thoracic rotations remain harmonic in every gait velocity. Voloshin (2000) studied the influence of gait speed on the heel strike that initiated shock waves and discovered that the dynamic loading to the musculoskeletal system will increase when the gait speed was increased. The speed of gait was found to reduce when walking in an unfamiliar place or walking with the eyes closed (Assaiante et al., 1989; Nadeau et al., 2003).

2.5 Body balance and falls

2.5.1 Introduction

Many factors will result in falls, but all falls occurred as a consequence of balance disorder. As such, the correlation between body balance and falls is studied and reported in this section.

2.5.2 The correlation between body balance and falls

During walking, the central nervous system always struggles to obtain a dynamic balance of upper torso during the swing phase of walking (Winter et al., 1990). Therefore, a human is always challenged to remain balanced during gait due to most body weight being positioned at two-thirds of their body height above the ground (Kavanagh et al., 2004). The centre of gravity will be shifted sideward when the human body part shifts to one side without a compensation of body weight by other body part of the equal weight. Shifted body part will increase the risk of body to topple as the centre of gravity is displaced outside its base of support (Schafer, 1987).

According to the study of Winter (1990; 1995) and Winter et al. (1993), gait is a continuous state of imbalance, and the only way to prevent falls is to position our swinging foot ahead of and lateral to the forward-moving centre of gravity. Two-thirds of the total body weight is centred in the upper body and store a significant amount of potential energy. If the trunk is not controlled in an upright position, this potential energy can easily be converted to kinetic energy to induce falls (Kuo, 2002).

According to David et al. (1990), the balance control of ageing people degenerates, thus falls represent a major health problem in elderly. According to Horak (2006), the control of body posture is a complex human dynamic sensorimotor interaction. Postural orientation and postural equilibrium were two functional goals in postural behaviour. Postural orientation aligns the trunk and head with gravitational force, condition of floor surfaces, visual reaction due to environmental stimulation and internal references. Postural equilibrium coordinates the body movement to stabilise the centre of body mass when the body is subjected to external perturbation or self-initiated body action that will cause body balance disorder.

2.6. Biomechanics of gait

2.6.1 Introduction

Biomechanics is a scientific study of biological systems that is concerned with the behaviour of physical bodies when subjected to internal forces (i.e., muscles generated forces) or to external forces. Based on Newton's second law of motion, these forces will induce accelerations on the biological system. Gait dynamics may be useful in providing insight into the neural control of human locomotion. The difference in trunk acceleration may affect the gait stability. This section reports the literature review outcomes on the gait speed and trunk acceleration in human gait.

2.6.2. Gait dynamics

Evidence showed that gait speed will affect gait stability (Bhatt et al. 2005; Dingwell and Marin, 2006). Trunk plays a crucial dynamic function in undermining accelerations accomplished during walking to ensure the stability of the head and visual platform (Winter, 1995; Menz et al., 2003; Prince et al., 1994). Hausdorff (2007) reported that stride-to-stride fluctuations of gait would increase the risk of falls and gait fluctuations can be detected by an accelerometer (Kobsar, 2012).

Kavanagh et al. (2004) performed a study on upper body accelerations of elderly and young men in human gait as shown in Figure 2.5. It was found that elderly subjects have lower critical peak positive anterior-posterior (AP) trunk acceleration during push-off and higher peak negative AP head and trunk accelerations after heel contact. Old adults also experienced slower time delay between the trunk and head accelerations in AP direction in comparison to young adults.

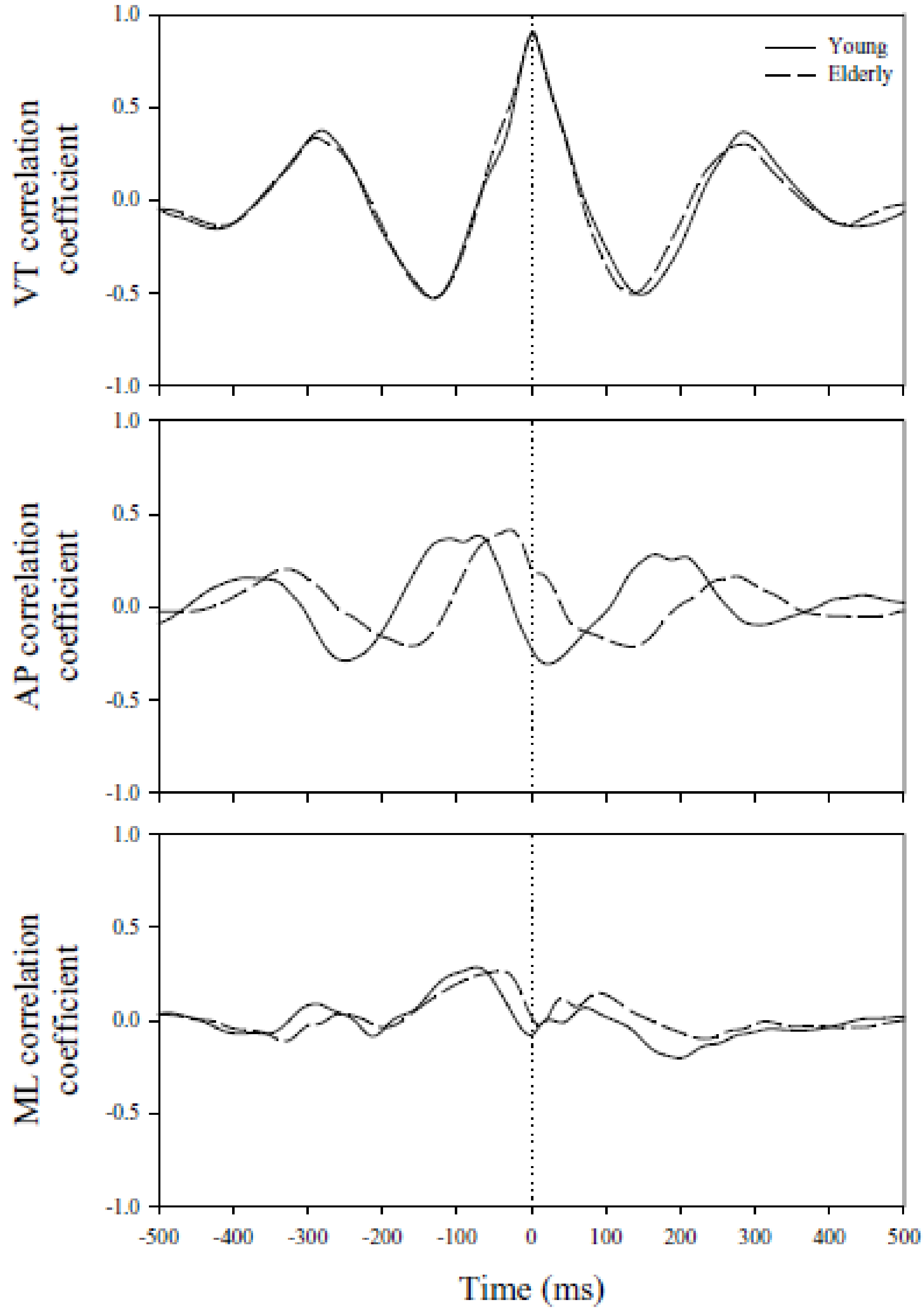


Figure 2.5: Ensemble averages of correlation coefficients between head-trunk accelerations in the vertical (VT), anterior-posterior (AP) and medial-lateral (ML) directions calculated over a full gait cycle (Kavanagh et al., 2004)

2.7 Techniques used to quantify gait

2.7.1 Introduction

Accelerometry is a technique for quantifying movement patterns using accelerometer-based systems. Activities monitored using accelerometers provide data regarding movement characteristics. This section reviews the current applications of accelerometer in the study of gait.

2.7.2 Applications of accelerometry in gaits related research

Van Schooten et al. (2015) reported that using accelerometer to capture trunk accelerations could provide useful information related to daily-life activities. This information can be used to reduce the risks of falls. Lu et al. (2017) found that smartphones equipped with accelerometers can accurately recognise physical activities of an individual to determine the correlation between physical activities and health. Kavanagh and Menz (2008) reviewed the use of accelerometer technology to investigate gait-related movement patterns and addressed issues of acceleration measurement for experimental design. They concluded that accelerometry can provide an accurate and reliable measurement of gait parameters and segmental accelerations of the body.

Mathie et al. (2004) reviewed the use of accelerometer-based systems in different movements which include gait, sit-to-stand transfers, postural sway and falls. The study outcome concluded that accelerometry is a tool that is suitable for long-term monitoring of free-living subjects as this method can provide reliable motion records of unconstrained subjects at low cost. Many of these functions can be carried out using a single triaxial accelerometer worn at the waist. Along this research direction, Giuffrida et al. (2008) selected KinetiSense system (Cleveland Medical Devices, 2011) to collect the body acceleration data of test subjects. The accuracy of the KinetiSense system was validated by Doan (2015), Professional Engineer at Engineering and Human Performance Lab by using 24 healthy young adults and performed 8 different actions. The result showed that, Kinetisense is a highly reliable motion capture system.

Yang and Hsu (2010) reported that most of the motion sensors were placed at the waist because the waist is close to the centre of mass and the trunk occupies the most mass of a human body. The measurement taken by a single sensor at this location can well represent the primary human motion. Besides, from an ergonomic point of view, sensors can easily be attached to or detached from a belt around waist level (Yang and Hsu, 2009; Karantonis et al., 2006; Sekine et al., 2000).

2.8 Findings from literature review

In this chapter, falls related research is briefly reviewed and can be summarised as follows:

1. Falls are a major public health problem particularly among older people as falls can result in deaths, injuries, hospitalisation, the increased of

public and personal medical cost and also affect the self-confidence of the fallers. Therefore, immediate preventive measures have to be taken to reduce the risks of falls.

2. The falls detection system is used to alert the caregiver when a fall event has occurred. Much effort has been expended to develop falls detection system using sensors and remote sensing technology. The accuracy of these systems was evaluated. Falls detection system with precision sensing technology and effective fall detection algorithm is possible to yield 100% sensitivity.
3. To reduce the harm to the victims of falls, fall prediction systems have been designed. However, high sensitivity fall prediction system is yet to be proposed to predict or eliminate falls by using wireless sensor technology.
4. Human gait is in a continuous state of imbalance. The lower limbs maintain the balance of body in human gait with the help of the sensory-motor system. The degradation of physiological functions, diseases and medication will impair balance control in human locomotion.
5. There is an association between balance disorder and falls. The body weight is centred in the upper body and stores a large amount of potential energy. The risk of fall increases if the body centre of gravity is displaced outside of the base of support.
6. Balance disorder is associated with gait speed and trunk acceleration. Therefore, trunk acceleration can be used as a parameter in studying the dynamic balance of gait.

7. An accelerometer can provide accurate and reliable measurements of trunk acceleration. Therefore, accelerometry is selected in this research to capture trunk acceleration for normal and abnormal gaits..

Based on the literature review, it is understood that fall detection is sometime too late to rescue the elderly people that could result in injuries or fatal conditions. On the other hand, it is challenging to design a real-time fall prediction system as many factors can induce falls. These factors include health conditions, floor surface conditions, and other unpredictable parameters. Similarly, it is challenging to measure the accuracy of a designed prediction algorithm. As a result, this research project explores the possibility of developing a fall reduction system which is an intermediate solution between fall detection and fall prediction (Figure 2.6). It is hypothesized that gait disorder will induce higher trunk acceleration while long period of high trunk acceleration will increase the risk of falls. Simulated normal gait and abnormal gait trunk acceleration data may provide some implications to confirm the hypothesis.

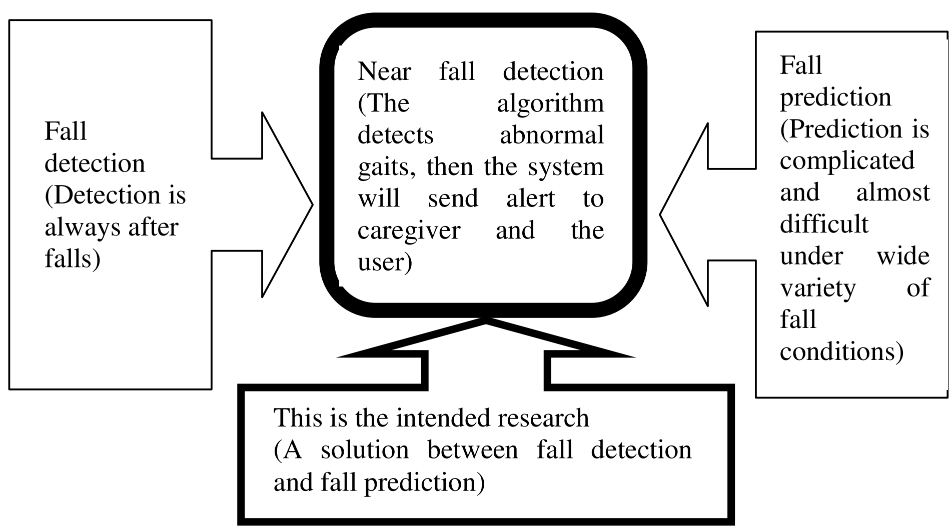


Figure 2.6: Scope of the research

CHAPTER 3

METHODOLOGY

3.1 Introduction

Two simulated experiments, namely normal gait experiment and abnormal gait experiment, were proposed to capture the trunk acceleration data among young and elderly cohorts. The trunk acceleration data collected were analysed statistically to investigate the relationship between human gaits with falls. The procedures used in each simulated experiment were explained in detail. Lastly, the details of test subjects (i.e., young and elderly) involved in the simulated experiments were presented. The relationship between trunk acceleration in human gaits with falls will be exploited to design fall reduction algorithms in Chapter 5.

3.2 Proposed simulated experiments

Human gait is defined as human biped locomotion. For ease of understanding, human gaits are the various ways in which a human can walk. Generally, human gait is classified into normal gait and abnormal gait. Normal gait is defined as a stable gait cycle that demonstrates a consistent gait pattern throughout the gait. Meanwhile, abnormal or unstable gait is defined as a result of balance disorder during walking. The gait cycle is inconsistent and fluctuating.

3.2.1 Experimental setup to capture and analyse trunk acceleration

Figure 3.1 shows the block diagram of KinetiSense wireless sensor system (Cleveland Medical Devices, 2011) used to capture and analyse the trunk acceleration in human gait.

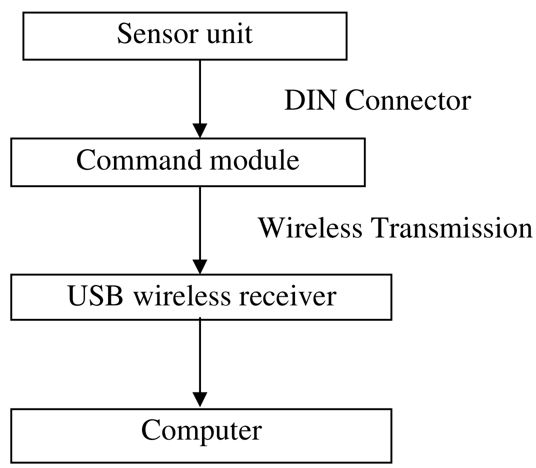


Figure 3.1: KinetiSense wireless sensor system

KinetiSense wireless sensor system consists of the following components:

1. Sensor unit: The sensor unit consists of a tri-axial accelerometer and a gyroscope. The sensor unit is used to capture the trunk acceleration in the simulated normal and abnormal gait experiments. The tri-axial accelerometer is orthogonally arranged to calculate the linear acceleration of the human trunk along x-, y-

and z-axis in the unit of g where 1g is equivalent to 9.8 m/s^2. Note that x-, y- and z-axes represent medio-lateral (ML) direction, anterior-posterior (AP) direction and vertical (VT) direction, respectively, as shown in Figure 3.2.

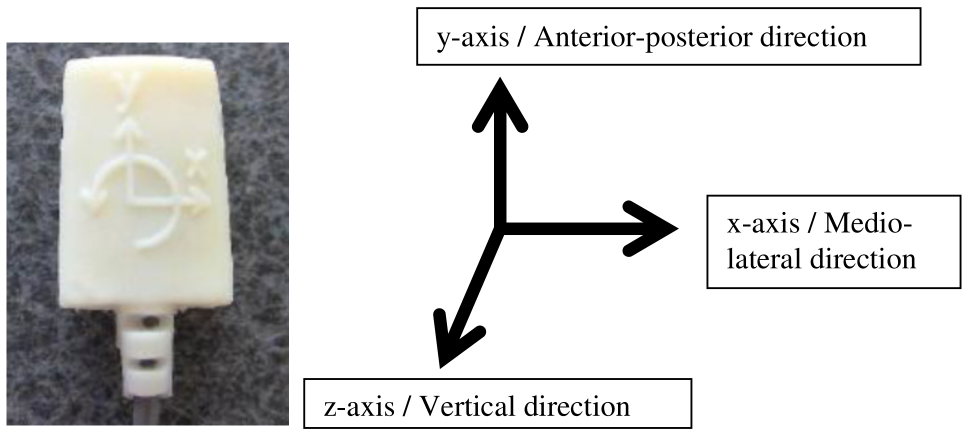


Figure 3.2: Orientations of the tri-axial accelerometer axes

2. Command module: The command module is shown in Figure 3.3. The command module receives acceleration data from the tri-axial accelerometer through a DIN connector and transmits the data to a computer through its wireless communication circuit. Full-duplex data transmission is employed where both end devices (i.e., command module and computer) can send and receive signals at the same time. The command module has five DIN connector sockets that allow the module to connect to five sensor units simultaneously.

Figure 3.3: The command module

3. DIN connector: The DIN connector refers to a connector that meets the DIN standard. The DIN connecter is used to transmit the acceleration data from the tri-axial accelerometer to the command module as shown in Figure 3.4.

Figure 3.4: Tri-axial accelerometer is connected to command module using DIN connector

4. USB wireless receiver: As shown in Figure 3.5, USB wireless receiver is a device attached to a computer to receive the accelerometer data from the transmitter of the command module. 2.4 GHz radio transmitter receiver system is embedded inside the command module enable real-time wireless data transmission to a computer.

Figure 3.5: USB wireless receiver attached to a computer

5. Computer: A computer is used to receive and analyse real-time trunk acceleration data from the command module using KinetiSence biokinetic analysis system software and USB wireless receiver. As shown in Figure 3.6, the KinetiSence biokinetic analysis system software is installed in the computer where the data can be viewed, processed and saved.

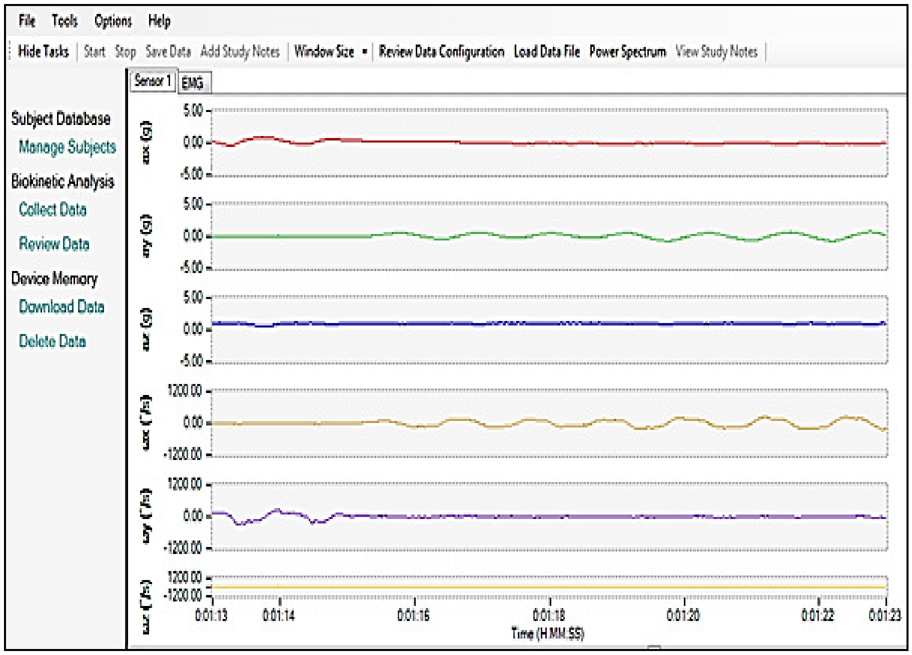


Figure 3.6: KinetiSence biokinetic analysis system software

Overall, the tri-axial accelerometer is attached to the command module using the DIN connector and sampled at 128 Hz with 12-bit resolution to capture the trunk acceleration of the test subjects for medio-lateral direction, anterior-posterior direction and vertical direction. The data acquisition starts after switching on the command module while the USB wireless receiver is linked to the computer. After the KinetiSense device connection is setup, sensors will be detected and acceleration data will be received and analysed by the KinetiSense software and IBM SPSS statistical analysis software.

3.2.2 Method to wear the tri-axial accelerometer

As shown in Figure 3.7, test subjects were instructed to wear a tri-axial accelerometer connected to a command module through the DIN connector at the waist position. The command module must be securely fixed at the waist position to achieve consistent orientation of the accelerometer as different orientations will produce inconsistent readings.

Figure 3.7: Subject wears the three axes wireless accelerometer at the waist position

3.2.3 Simulated normal gait experiment

The procedures to capture the trunk acceleration data in normal gait experiment are listed as follows:

1. A 10 meters long of dry and flat floor with starting and ending lines was prepared as shown in Figure 3.8.

Figure 3.8: A 10 meters long of flat and dry floor for normal gait experiment

2. Test subject was instructed to standby at the starting line of the 10 meters long of dry and flat floor as shown in Figure 3.9.

Figure 3.9: Test subject standby at the starting line for simulated normal gait experiment

3. Two helpers were positioned at the starting line and the end line respectively of the 10-meter walkway to assist and monitor the trunk acceleration data capturing process.

4. Test subject was instructed to switch on the command module and walk normally through the 10-meter walkway.

5. The walking process was repeated twice to confirm the reliability of the experimental method and the consistency of the devices used in the experiment.

6. The trunk acceleration data of the test subject in normal gait experiment was collected and stored in the computer connected to the command module wirelessly.

   Throughout the simulated normal gait experiment, video was captured.

3.2.4 Simulated abnormal gait experiment

The procedures to capture the trunk acceleration data in abnormal gait experiment are listed as follows:

1. An instrumented treadmill was needed to simulate the abnormal gait of test subjects.

2. As test subjects will experience gait disorder which results in falls, a safety belt was placed on a built mechanical structure constructed around the treadmill to ensure the safety of test subjects as shown in Figure 3.10 and Figure 3.11.

Figure 3.10: Supporting structure to place the safety belt

Figure 3.11: The safety belt is attached to the supporting structure

3. Two helpers were positioned to make sure the test subject had properly tightened the tri-axial accelerometer, the command module and the safety belt.

4. Test subject was instructed to get used to the treadmill by walking on the treadmill for 20 minutes. The starting belt-conveyer moving speed was set to 1.1 m/s (i.e., 4 km/h) as this speed was comfortable for all of the volunteers during the trial.

5. A number of 10-milimeter round stickers were randomly pasted on the treadmill as shown in Figure 3.12.

Figure 3.12: Round stickers are randomly pasted on the treadmill

6. Test subject was instructed to avoid round stickers while walking on the treadmill to simulate abnormal gait condition as shown in Figure 3.13.

Figure 3.13: Subject need to avoid stepping on randomly pasted round stickers to simulate abnormal gaits

7. Near fall condition will occur if the test subject continues to experience gait disorder. Near fall condition can be observed when the safety belt that supports the subjects from fall is in tension as shown in Figure 3.14. Once safety belt is in tension, the helpers will stop the treadmill. A strain gauge system that consists of sensor whose resistance varies with applied force and buzzle (alarm) was developed and installed at the supporting belt to measure the tension of the belt. When the supporting belt is in tension, the electrical resistance of the sensor will changed and triggered the alarm to alert the helpers to stop the treadmill. Qualification test was carried out before the experiment to ensure imbalance between the tensions in various directions of falls (ML and AP directions) is not affect the sensitivity of the strain gauge.

Figure 3.14: The safety belt that supports the subjects from fall is in tension

8. The walking process was repeated twice for each test subject to confirm the repeatability of the experimental method and the consistency of the devices used in the experiment.

9. The trunk acceleration data of the test subject in abnormal gait experiment was collected and stored in the computer connected to the command module wirelessly.

Throughout the simulated abnormal gait experiment, video was captured.

3.3 Test Subjects

A total of 144 test subjects that consist of young and elderly adults participated in the simulated normal gait experiment and abnormal gait experiment. The test subjects consisted of 84 males and 60 females with ages between 20 to 70 years old, heights between 154cm to 180cm and weights between 43kg to 70kg. Test subjects are classified into young adult if the test subject's age is less than or equal to 55 years old and elderly adult otherwise. Out of 144 test subjects, there are 80 young adults and 64 elderly adults. Notice that 80 young adults consist of 48 males and 32 females. Meanwhile, 64 elderly adults consist of 36 males and 28 females.

3.3.1 Health condition of the test subjects

Diseases and health status will affect gait stability. For example, a stroke will affect dynamic balance during walking. An et al. (2017) reported that hemiplegic patients after stroke would demonstrate spatiotemporal asymmetrical gait patterns. Impaired balance is common in neurological disorders. Barr et al. (2017) compared balance, mobility, gait and stepping reactions between people with cervical dystonia and healthy adults. The study outcomes have shown that there was a significant difference between individuals with cervical dystonia and healthy people. People with cervical dystonia have demonstrated deficits in balance, gait and stepping reactions and expressed higher fear of falling (Barr et al., 2017). Screening was carried out to make sure all test subjects have no gait disturbance by observing their normal gait for a 10-meter walk on the dry and flat floor. The screening can eliminate the possibility of pathological change in that body that may affect the experiment result. Informed consents were obtained from all test subjects.

3.3.2 Informed consent and safety consideration

Before conducting simulated normal gait and abnormal gait experiments, all test subjects were briefed in detail on the purpose of the research, experimental procedure and the known risk of fall. All test subjects understand that the participation in this study is voluntary. The participation may be stopped if the test subjects change their mind throughout the experiment. The test subjects were informed that their privacy (e.g. name, gait and health condition) is protected; however the collected trunk acceleration data of the test subjects would be studied and analysed by the researchers for academic research purposes.

There are four helpers who assisted in the simulated normal gait and abnormal gait experiments. In normal gait experiment, two assistants took care of the data collection system while the other two helpers assisted the test subjects throughout the experiments. In abnormal gait experiment, the helpers are responsible to ensure all test subjects wore safety belt correctly. Besides that, the test subjects and the assistants were allowed to stop the experiment if there was any uncontrolled situation such that the risk of fall is high. In abnormal gait experiment, one helper took care of data collecting system, one helper controlled the operation of the treadmill and two remaining helpers assisted the test subjects if the balance system of the test subject is out of control.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results of simulated normal and abnormal gait experiments. Trunk acceleration data of 144 test subjects was collected in the simulated normal and abnormal gait experiments. Times series data is plotted and explained at the beginning of this chapter. Subsequently, the statistical analysis outcomes based on positive peak values of trunk acceleration in medio-lateral direction, anterior-posterior direction and vertical direction are presented. After that, the conditions of the test subjects when experiencing abnormal gait are described. Lastly, the results of the simulated normal and abnormal gait experiments are discussed.

4.2 Trunk acceleration data of test subjects

4.2.1 Simulated normal gait experiment

In simulated normal gait experiment, video recording images showed the test subject swayed backward and forward consistently as an inverted pendulum to maintain the trunk in an upright position. Trunk acceleration values are considered as positive and negative for forward direction and backward direction respectively as shown in Figure 4.1.

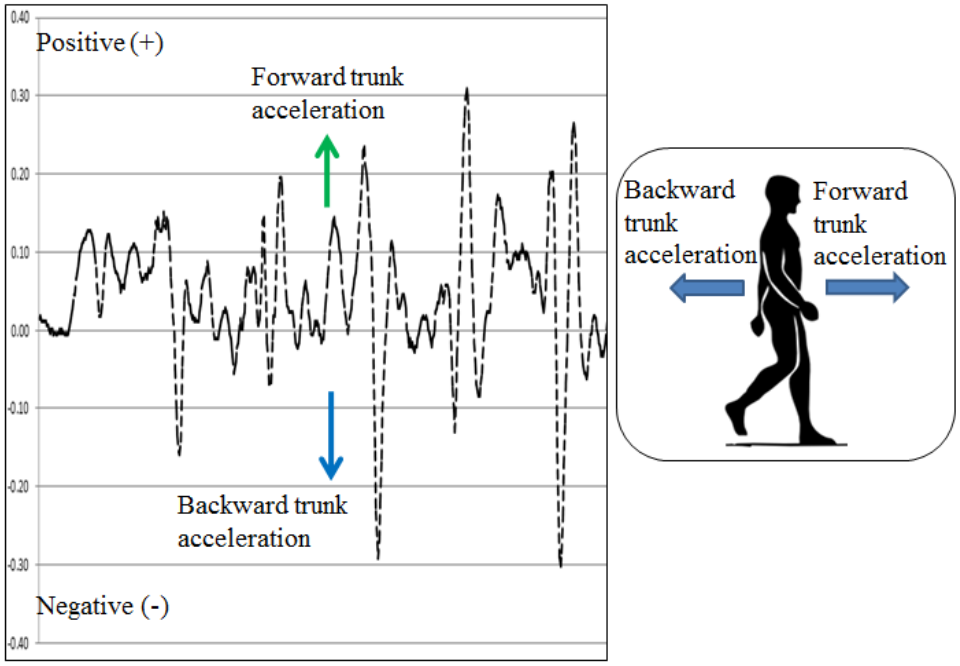
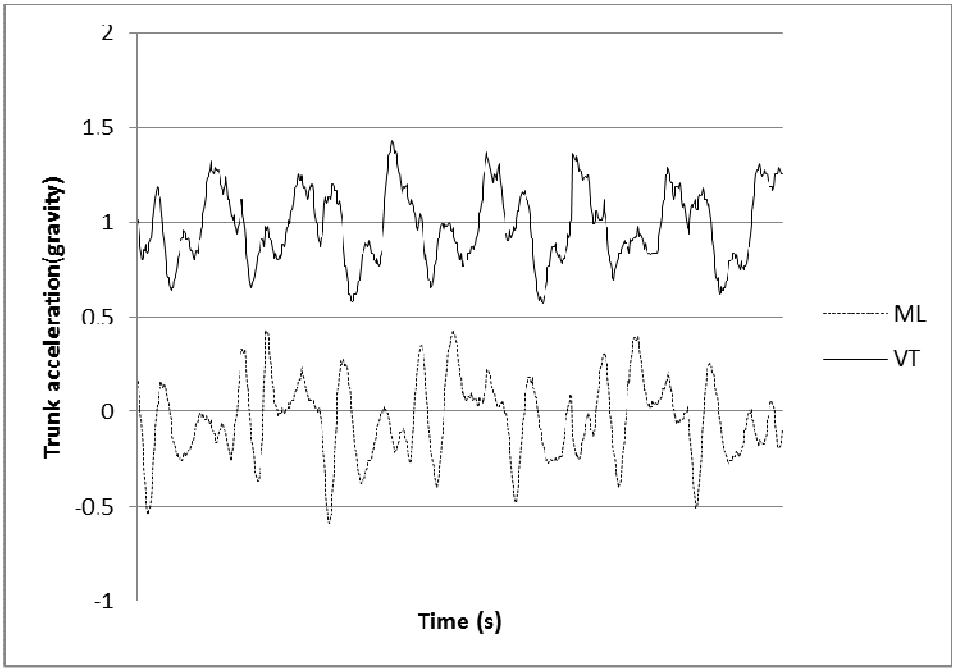
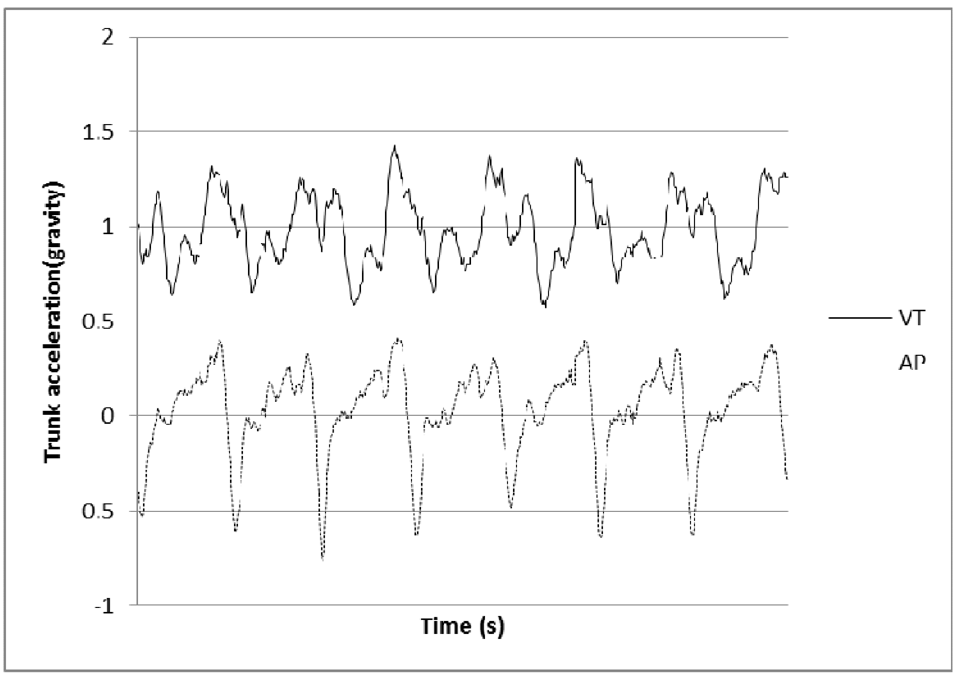


Figure 4.1: Trunk acceleration data of test subjects in simulated normal gait experiment

A typical cyclic change of individual test subject's trunk acceleration in ML, AP and VT directions is illustrated in Figure 4.2 (a) and Figure 4.2 (b). The same experiment method was repeated twice to confirm the reliability of the experimental method and the consistency of the devices used in the experiments. The following observations were made:



(a)



(b)

Figure 4.2: Time series graph of individual test subject acceleration in normal gait experiment in (a) Mediolateral (ML) and Vertical (VT) direction, (b) Vertical (VT) direction and Anterior-posterior (AP) direction

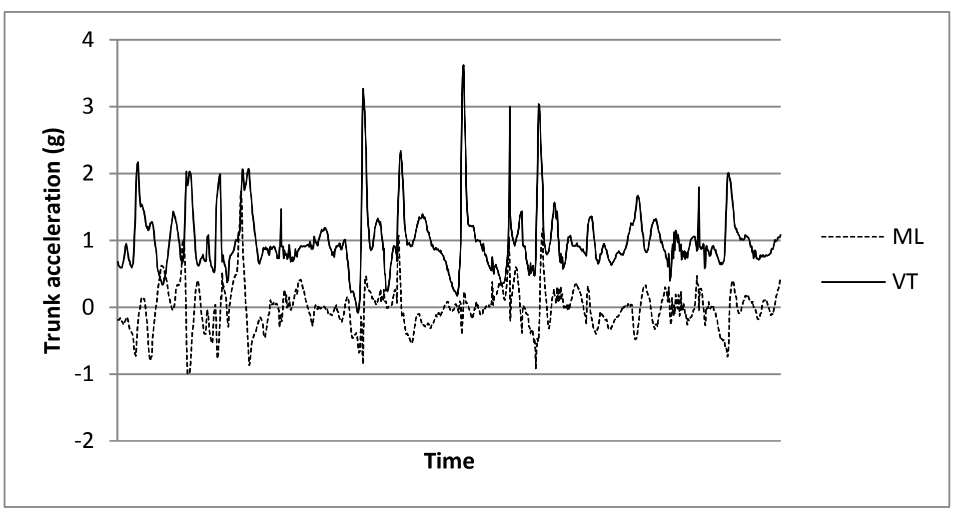
1. Individual trunk acceleration time series graphs in normal gait showed consistent periodical gait cycle pattern and similar peak-to-peak amplitude in every gait cycle.

2. Same test subject demonstrated similar trunk acceleration pattern when the experiment was repeated twice.

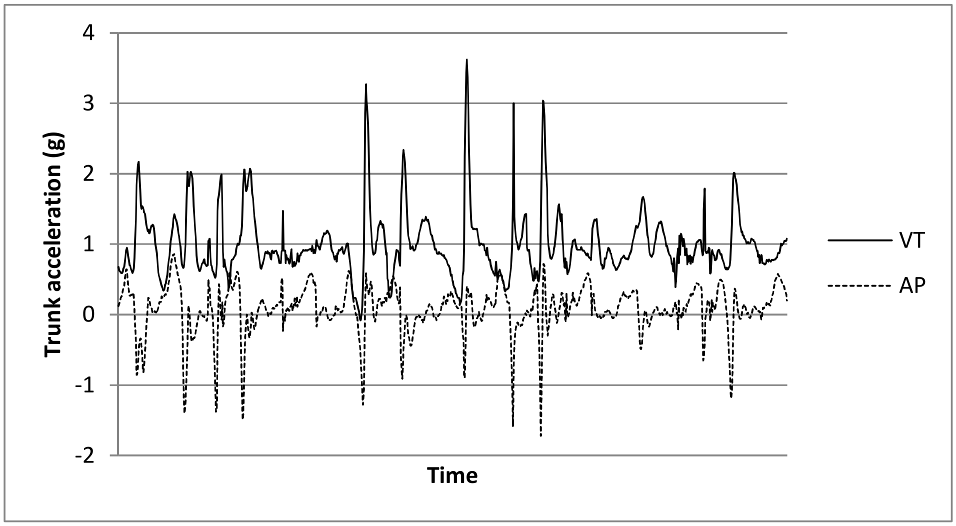
3. The duration of the gait cycle and the trunk acceleration amplitude for every individual test subject were similar, but different from other test subjects.

4.2.2 Simulated abnormal gait experiment

Figure 4.3 (a) and Figure 4.3 (b) illustrate typical individual trunk acceleration graph for abnormal gait. Time series graph of individual test subject acceleration in abnormal gait experiment showed irregular gait cycle and varying peak-to-peak amplitude in every gait cycle.



(a)



(b)

Figure 4.3: Time series graph of individual test subject acceleration in abnormal gait experiment in (a) Mediolateral (ML) and Vertical (VT) direction, (b) Vertical (VT) and Anterior-posterior (AP) direction

4.3 Statistical analysis of trunk acceleration result in simulated normal gait and abnormal gait

Based on line graphs in Figure 4.2 (a) and (b), the positive and negative peak trunk acceleration values are almost symmetrical. Therefore, either positive or negative peak trunk acceleration can be used in the study to confirm whether the trunk acceleration is one of the parameters that can be applied to classify normal and abnormal gait.

In this study, the maximum peak values of trunk acceleration in ML direction, AP direction and VT direction were analysed by using statistical analysis software, IBM SPSS.

Statistical analysis has been carried out to investigate the differences across the age ranges and genders between normal and abnormal gait trunk acceleration in ML, AP and VT directions. It was found that, all the P values are less than 0.05 indicating that there is significant difference between normal and abnormal trunk acceleration for all age ranges and genders.

Table 4.1 summarises the results of the maximum trunk acceleration analysis results for 144 test subjects by assuming that acceleration unit is g = 9.8 m/s^2. Trunk acceleration in gait can be written as $g_{i\epsilon\,(1,\ldots,N)}(trunk)i$, where N denotes sampling time in second. Statistical data of normal and abnormal trunk accelerations based on 99% confidence interval (CI). The usage of 99% of CI is to have 1% error/accuracy, for example, to decide abnormal trunk acceleration.

Table 4.1: Statistical data of normal and abnormal trunk accelerations based on 99% confidence interval for 144 test subjects

TYPE OF GAITS	NORMAL			ABNORMAL		
DIRECTION	ML	AP	VT	ML	AP	VT
MEAN	0.51	0.46	1.64	1.31	1.73	3.56
CI FOR LB[1]	0.46	0.40	1.60	1.14	1.46	3.28
CI FOR UB[2]	0.56	0.51	1.69	1.48	1.99	3.83
MEDIAN	0.47	0.44	1.61	1.14	1.43	3.46
VARIANCE	0.04	0.06	0.04	0.33	0.83	0.86
STANDARD DEVIATION	0.21	0.25	0.20	0.58	0.91	0.93
MIN	0.06	0.03	1.39	0.54	0.07	1.65
MAX	1.14	1.06	2.24	2.94	4.50	4.52
RANGE	1.08	1.03	0.85	2.40	4.43	2.87
SKEWNESS	0.61	0.31	1.30	1.07	1.45	-0.22
KURTOSIS	0.38	-0.61	1.64	0.66	1.71	-1.58

(Notes)

1. CI for LB =99% Confidence Interval for Mean of Lower Bound
2. CI for UB = 99% Confidence Interval for Mean of Upper Bound

The statistical analysis results presented in Table 4.1 indicate the following observations:

1. The mean value of normal gait is lower than of abnormal gait.
2. The standard deviation of the normal gait is relatively smaller than of abnormal gait in all three directions. Small standard deviation in normal gait indicates that the trunk acceleration tends to be close to the mean value, while a high standard deviation observed in abnormal gait indicates that the trunk acceleration is spread out over a wider range of values.
3. The range in normal gait is smaller as compared to abnormal gait. This means that the difference between the maximum and minimum trunk acceleration in normal gait is lower.
4. The variance in normal gait is smaller as compared to abnormal gait.
5. The difference between mean and median is small in normal gait indicates that the collected data is symmetrically distributed. The mean is greater than the median in abnormal gait means that the distribution skews to the right.

For the data to be normally distributed, the skewness and kurtosis values should be in the range of -1.96 to +1.96 (Chua, 2013). Skewness is a measure of symmetry. Data set is symmetric if it looks the same to the left and right of the centre point. Meanwhile, kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. Data sets with high kurtosis tend to have outliers. In normal and abnormal gait experiments, the trunk accelerations distribution data for ML, AP and VT directions are normally distributed because the skewness and kurtosis values are within the normal distribution range. In general, statistical analysis performed after the experiments indicated that normal gait demonstrates smaller trunk acceleration variability when compared to abnormal gait.

The mean value of normal and abnormal trunk acceleration in ML direction, AP direction and VT direction are plotted in Figure 4.4. The mean value comparison between normal and abnormal trunk accelerations indicates that all mean values of trunk acceleration in ML direction, AP direction and VT direction of abnormal gait are greater than normal gait.

In addition, it is observed that, the P values of significant test for ML, AL and VT directions between normal and abnormal trunk accelerations for 144 test subjects are 0.030, 0.006 and 0.000 respectively. The P values are less than 0.05 indicated that, there is significant difference between normal and abnormal trunk acceleration.

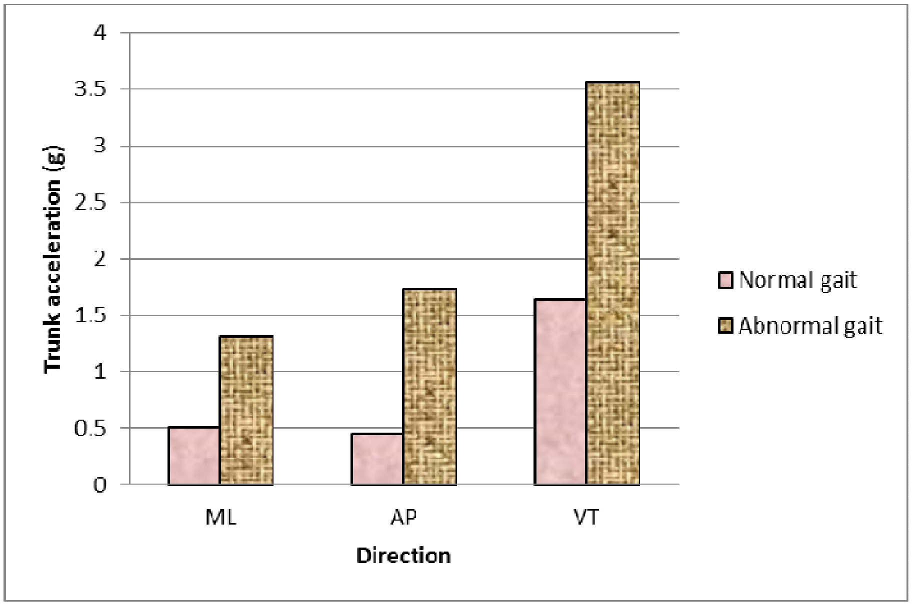


Figure 4.4: Comparison of mean value of trunk acceleration in ML, AP and VT directions between normal and abnormal gaits

Mean values of upper bound and lower bound trunk acceleration for values of normal gait and abnormal gait in ML, AP and VT directions are plotted in Figure 4.5. The ranges for ML, AP and VT shown in Figure 4.5 were obtained by subtraction of CI for UB and LB, where CI denotes confidence interval, UB denotes upper bound and LB denotes lower bound. The results showed that the upper bound normal gait trunk acceleration does not overlap with the lower bound abnormal gait trunk acceleration. No overlapping between upper bound of trunk acceleration in normal gait and lower bound of trunk acceleration in abnormal gait make it possible to classify gait into normal and abnormal based on trunk acceleration.

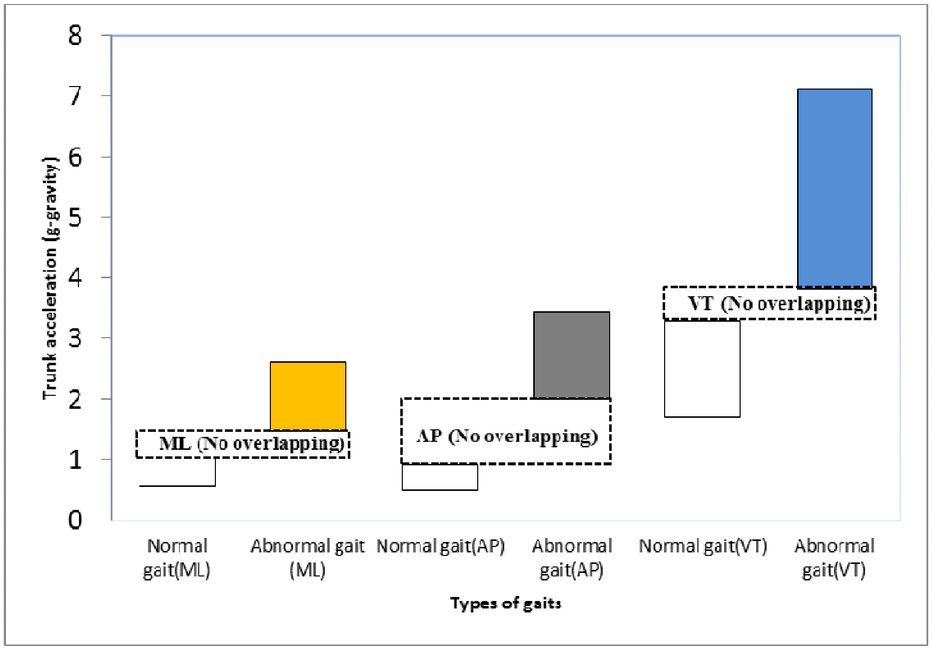


Figure 4.5: Mean Values of Upper Bound Normal Gait Trunk Acceleration do not overlap with Mean Values of Lower Bound Abnormal Gait Trunk Acceleration

Figure 4.6 shows the mean trunk acceleration value for elderly aged more than 55 and young subjects with ages between 20 to 55 years old. The comparison outcome indicates that there is no significant difference trunk acceleration of old and young test subjects.

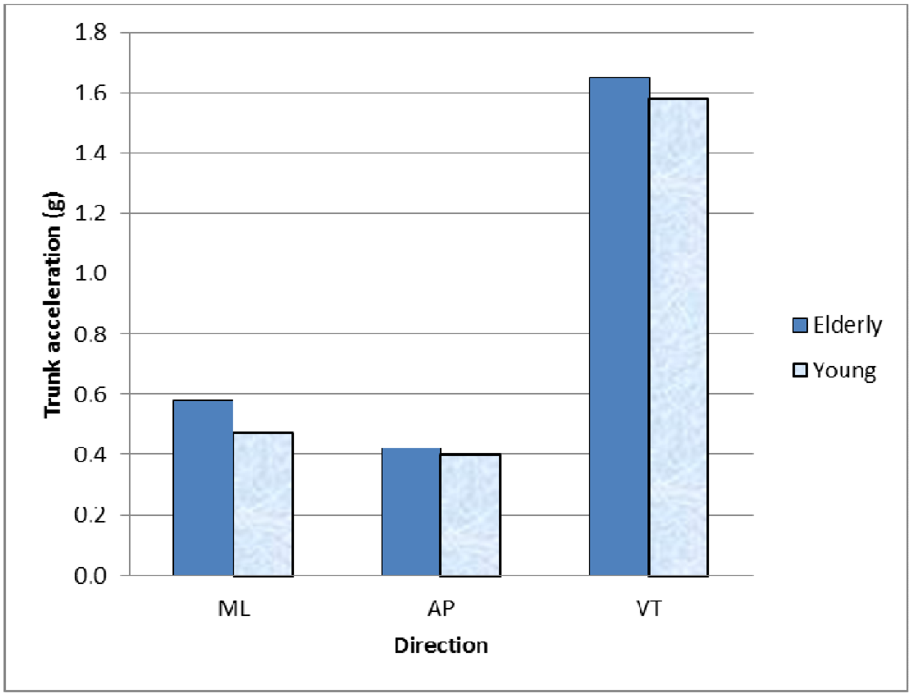


Figure 4.6: Comparison of Trunk Acceleration Mean Value Between the elderly (age > 55) and the young (age ≤ 55) in simulated normal gait experiment

Figure 4.7 illustrates the comparison of mean trunk acceleration value between male and female test subjects in simulated normal gait experiment. The comparison outcome shows that female test subjects have slightly higher mean trunk acceleration value with a small difference of less than 0.6g.

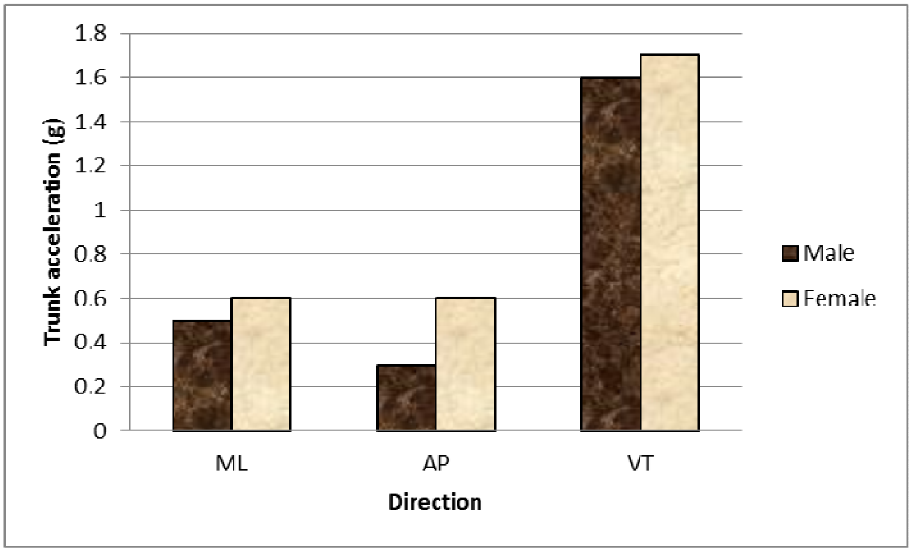


Figure 4.7: Comparison of mean trunk acceleration value between male and female test subjects in simulated normal gait experiment

As shown in Figure 4.8, normal gait produce periodical trunk acceleration. However, abnormal gait did not produced periodical trunk acceleration as shown in Figure 4.9. More precisely, the trunk accelerations for abnormal gait were random and not consistent. From Table 4.1, quantitative analysis result revealed that there is a significant difference between the maximum value of a normal gait and maximum value of abnormal gait trunk acceleration. Figure 4.10 compares the mean value of a normal gait and mean value of abnormal gait trunk acceleration.

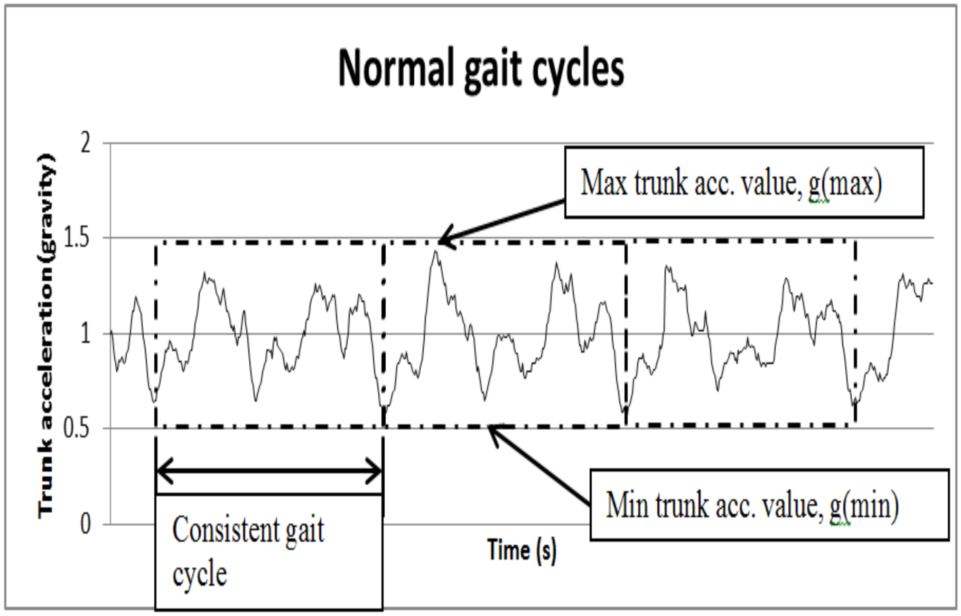


Figure. 4.8: Typical individual normal gait cycle

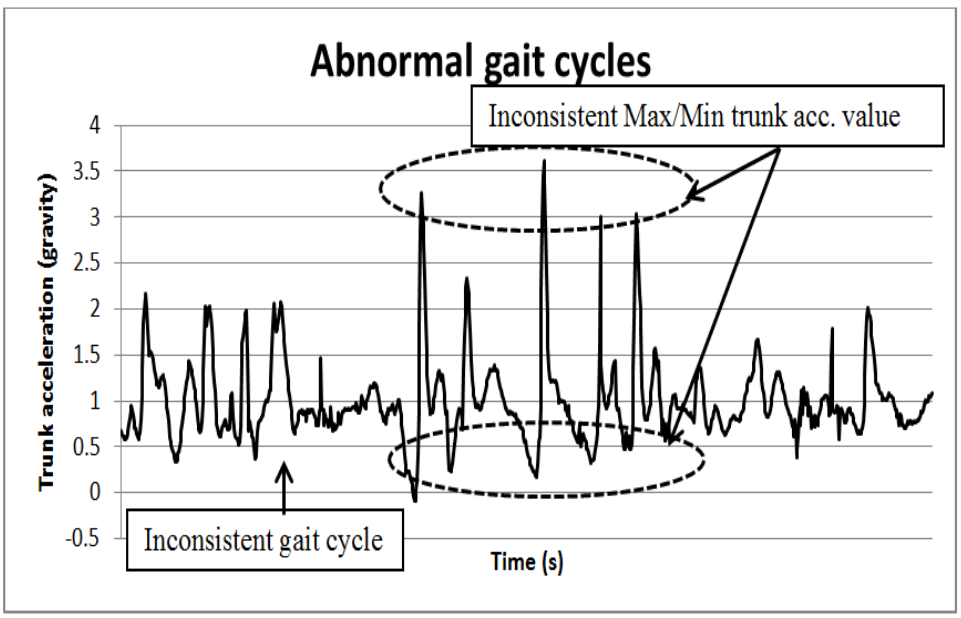


Figure 4.9: Typical individual abnormal gait cycle

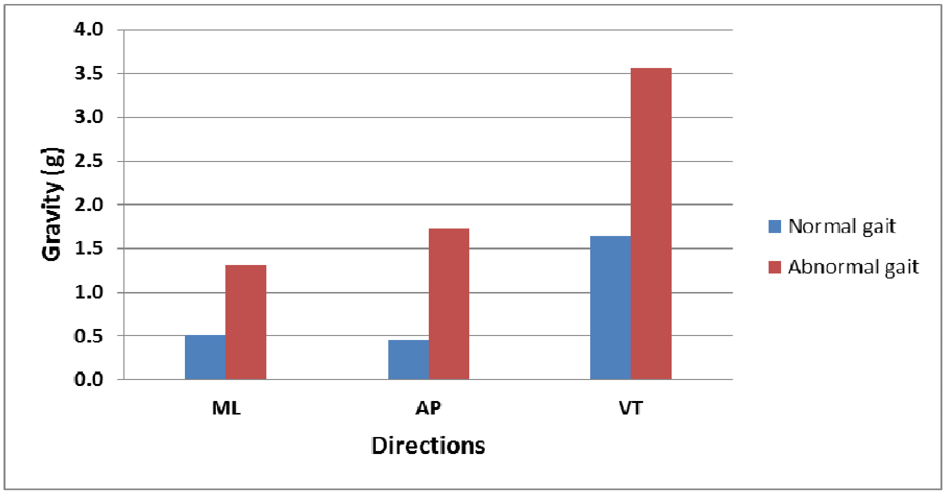


Figure 4.10: Comparison of mean value of trunk acceleration between normal gait and abnormal gait

From Table 4.1, Figure 4.8, Figure 4.9 and Figure 4.10, it is observed that the maximum trunk acceleration value in normal gait is smaller than maximum trunk acceleration value in abnormal gait. Besides that, the minimum trunk acceleration value in normal gait is also smaller than abnormal gaits minimum trunk acceleration value of abnormal gait.

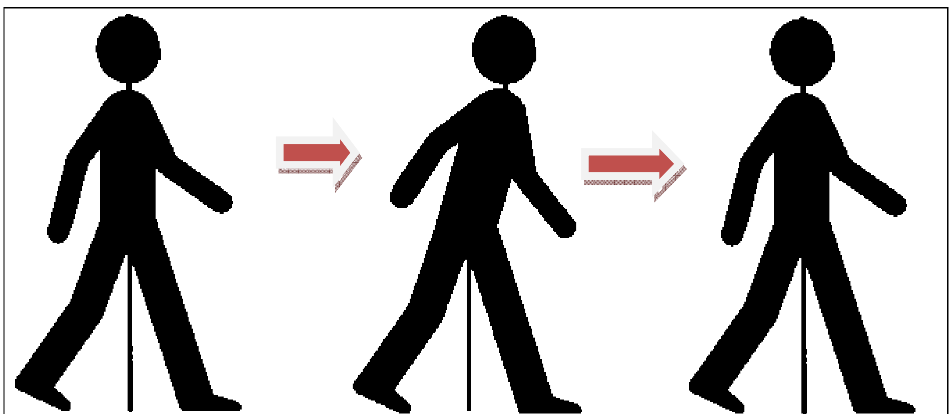
$$g(max)_{\text{normal gait}} < g(max)_{\text{abnormal gait}} \; ; \; g(min)_{\text{normal gait}} < g(min)_{\text{abnormal gait}}$$

4.4 Observation in abnormal gaits experiment recovery action when test subjects experienced gaits disorder

Two following conditions were observed in abnormal gaits experiment:

1. Test subject can recover from abnormal gait: This condition is illustrated in Figure 4.11. First, test subject started walking in normal gait at the beginning of the abnormal gait experiment. The trunk acceleration of the test subject was below the threshold value. Later, when the test subject tried to avoid stepping on the round stickers

pasted on the treadmill, they began to experience balance disorder. Thus, this leads to inconsistent gait cycles and higher trunk accelerations than the threshold value. Recovery action was taken to overcome balance disorder when test subject experienced abnormal gaits. Eventually, the test subject managed to recover from abnormal gait and the trunk acceleration back to normal gait trunk acceleration. Notice that several steps were needed to regain the normal gait.

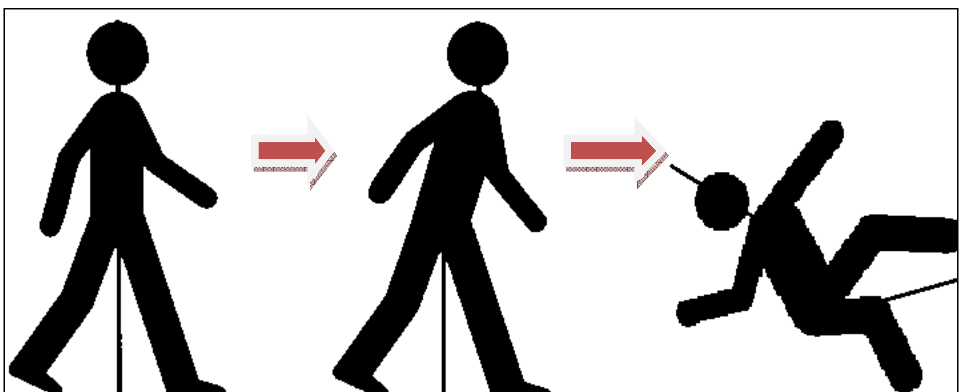


Start walking with a normal gait (Trunk acceleration below the threshold value).	Experiencing abnormal gait (Trunk acceleration exceed the threshold value for few times).	Recovery action takes place to overcome balance disorder and manage to return to normal gait (Trunk acceleration below the threshold value).

Figure 4.11: Abnormal gaits experiment: test subject is able to recover from abnormal gait

2. Test subject cannot recover from abnormal gait: This condition is illustrated in Figure 4.12. Test subject started walking in normal gait at the beginning of the experiment. The trunk acceleration of the test subject was below the threshold value. Later, when the test subject tried to avoid stepping on the round stickers pasted on the treadmill, they began to experience balance disorder. Thus, this leads to inconsistent

gait cycles and higher trunk accelerations than the threshold value. Recovery action was attempted to overcome balance disorder when test subject experienced abnormal gaits. However, the test subject failed to recover from abnormal gaits and experienced near fall after a few cycle of abnormal gaits. Table 4.2 shows the trunk acceleration values in near fall gaits in ML, AP and VT directions. As illustrated in Figure 4.13, the near fall trunk acceleration values are higher than abnormal gait trunk acceleration values. The near fall trunk acceleration values were obtained from CI for UB (99% Confidence Interval for Mean of Upper Bound) of abnormal gait trunk acceleration.



Start walking with a normal gait (Trunk acceleration below the threshold value).	Experiencing abnormal gait (Trunk acceleration exceed the threshold value for many times).	Experience near fall gait (Trunk acceleration exceed the threshold value for many occasions) and fall.

Figure 4.12: Abnormal gaits experiment: volunteer is not able to recover from abnormal gait and experience fall after experiencing many cycles of abnormal gaits

Table 4.2: Near fall gait trunk acceleration values for three directions

Direction	Near fall trunk accelerations
ML	1.48g
AP	1.99g
VT	3.83g

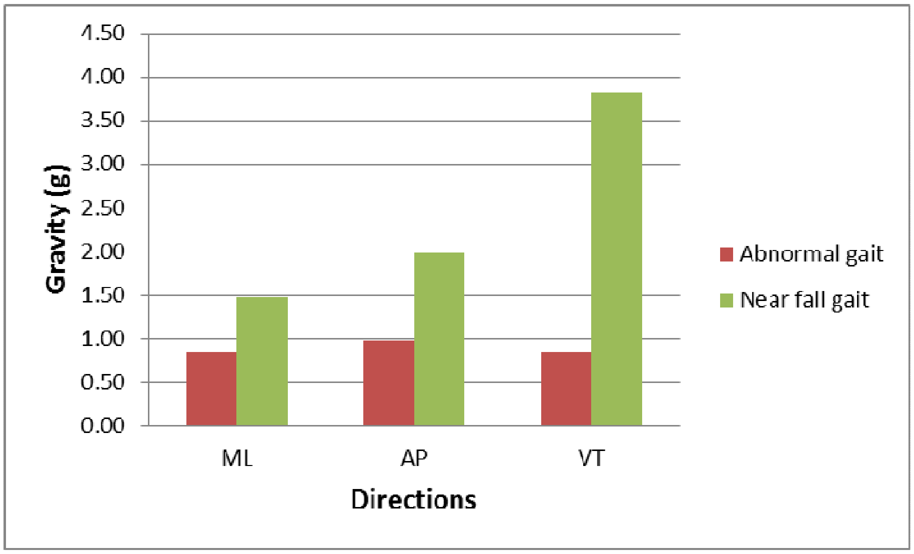


Figure 4.13: Comparison between CI for LB (Abnormal gait) wit CI for UB (near fall gait) trunk acceleration

4.5 An application of Newton's Second Law of motion in simulated normal and abnormal gait

According to Newton's second law of motion, the acceleration a is produced when a force F is applied to a mass M as shown in Equation (4.1).

$$F = M \text{ x } a \tag{4.1}$$

Thus, if the mass of the trunk M_{trunk} remains constant, the force of the trunk F_{trunk} will increase if the trunk acceleration a_{trunk} increases as shown in Equation (4.2).

$$a_{trunk} = F_{trunk} / M_{trunk} \quad (4.2)$$

The torque applied to the trunk T_{trunk} of the subjects can be calculated by Equation (4.3),

$$T_{trunk} = F_{trunk} \text{ x } R \quad (4.3)$$

where R denotes the height from the ground to the waist of the subject (i.e., the position where the accelerometer is located) as depicted in Figure 4.14.

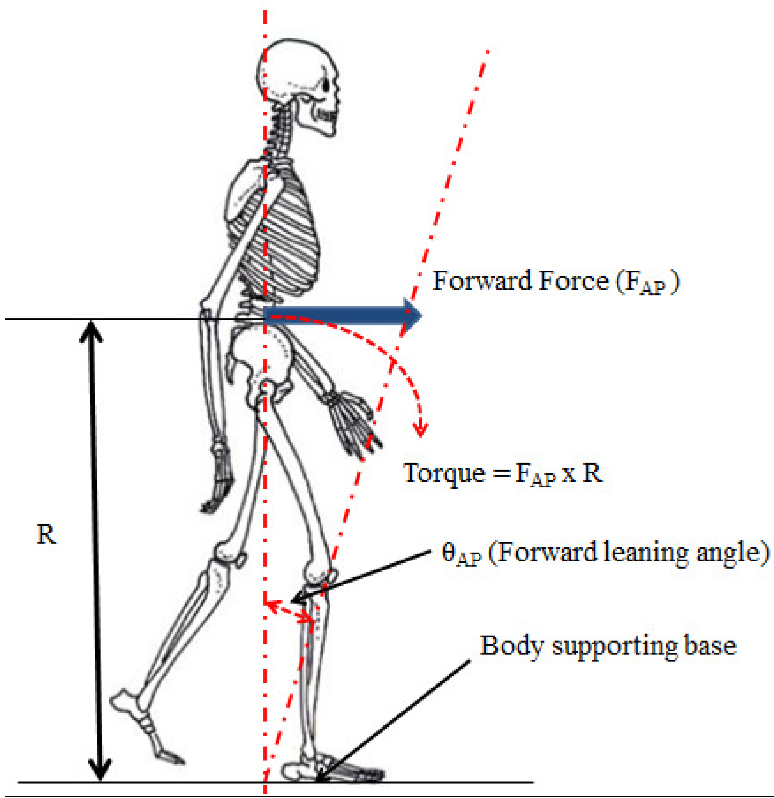


Figure 4.14: During walking, abnormal gait occur due to higher trunk force applied to anterior-posterior (AP) direction around the subject's waist

From Table 4.1, the statistical analysis result of the trunk accelerations a_{trunk} in normal gait for ML, AP and VT directions are 0.51g, 0.46g, and 1.64 g respectively. These values are much lower if compared to the mean values of trunk accelerations in abnormal gait where the trunk accelerations a_{trunk} in abnormal gait for ML, AP and VT directions are 1.31g, 1.73g and 3.56g respectively.

In the simulated normal gait and abnormal gait experiments, all test subjects walked in AP direction and as such the trunk force of test subject in AP direction F_{AP} and the trunk torque of test subject in AP direction T_{AP} were studied. By applying the trunk acceleration of test subject in normal gait for AP direction, a_{trunk} = 0.46g, in Equation (4.1) and Equation (4.3), $F_{AP(normal)}$ and $T_{AP(normal)}$ can be obtained as follows:

$$F_{AP(normal)} = M_{trunk} \text{ x } 0.46\text{g} \tag{4.4}$$

$$T_{AP(normal)} = M_{trunk} \text{ x } 0.46\text{g x } R \tag{4.5}$$

Similarly, by applying the trunk acceleration of test subject in abnormal gait for AP direction, a_{trunk} = 1.73g, in Equation (4.1) and Equation (4.3), $F_{AP(abnormal)}$ and $T_{AP(abnormal)}$ can be obtained as follows:

$$F_{AP(abnormal)} = M_{trunk} \text{ x } 1.73\text{g} \tag{4.6}$$

$$T_{AP(abnormal)} = M_{trunk} \text{ x } 1.73\text{g x R} \tag{4.7}$$

By calculating the ratio of $F_{AP(abnormal)}$ to $F_{AP(normal)}$ and the ratio of $T_{AP(abnormal)}$ to $T_{AP(normal)}$, it was found that the forward force F_{AP} and forward torque T_{AP} in abnormal gait are 376% larger than of normal gait. Table 4.3 shows the ratios of trunk force and trunk torque for abnormal gait and normal gait in ML, AP and VT directions.

Table 4.3: Ratio of abnormal gait and normal gaits in term of trunk forces in ML, AP and VT directions

Directions	**Ration of abnormal gait trunk force and normal gait trunk force (%)**
ML (Medio-lateral)	257%
AP (Anterior-posterior)	376%
VT (Vertical)	217%

Results show that abnormal gait trunk acceleration in ML, AP and VT directions are much higher than normal gait trunk acceleration.

Trunk acceleration is the rate of change of trunk velocity with respect to time as shown in Equation (4.8).

$$a_{trunk} = \Delta(v_{trunk2} - v_{trunk1}) / \Delta t \tag{4.8}$$

When the trunk acceleration a_{trunk} increases while the mass of the trunk remains constant, the trunk force will increase. The increase of trunk acceleration will result in a big change of velocity in a short period. Thus, this high-velocity change in a short period may topple the test subject with a torque that will result in gait disorder or fall.

4.6 The association of forward trunk acceleration with trunk leaning angle

This section discusses the relationship of forward trunk acceleration with trunk leaning angle. In simulated normal and abnormal gait experiments, it was observed from Figure 4.14 that, the trunk is inclined to the front when the test subject is moving forward. Trunk leaning angle is defined as the angle between the trunk and the vertical axis of the test subject which is at the right angle to the floor. The forward trunk leaning angles can be derived by the torque applied to the waist of test subject induced by forward anterior-posterior direction trunk force as illustrated in Figure 4.14. Angle between the vertical axis and the trunk vertical plane is defined as leaning angle, $\theta_{AP,}$ an angular velocity caused by falls or near falls can be denoted as $\omega_{AP} = d\theta_{AP}/dt$. Thus, the forward velocity can be obtained by multiply angular velocity (v_{AP}) with R (Figure 4.14), $v_{AP} = \omega_{AP} \times R$ and the angular acceleration (α) is $d\omega_{AP}/dt$ or $d^2\theta_{AP}/dt^2$. Subsequently, the forward force F_{AP} applied to the mass center of the trunk can be computed using Equation (4.9).

$$F_{AP} = M_{trunk} \times (dv_{AP}/dt) \tag{4.9}$$

When the subject stops suddenly in the forward direction which might be followed by fall or near fall, the F_{AP} can be denoted as in equation 4.10,

$$F_{AP} = M_{trunk} \times R \times d\omega_{AP}/dt \tag{4.10}$$

Meanwhile, the forward leaning torque T_{AP} at the waist of test subject can be computed using Equation (4.11).

$$T_{AP} = R \text{ x } M_{trunk} \text{ x } dv_{AP}/dt = M_{trunk} \text{ x } R^2 \text{ x } d\omega_{AP}/dt \qquad (4.11)$$

Lastly, the relationship between anterior-posterior trunk acceleration and forward angular acceleration is represented in Equation (4.12).

$$a_{AP} = R \text{ x } d\omega_{AP}/dt \quad = R \text{ x } d^2\theta_{AP}/dt^2 \qquad (4.12)$$

In a nutshell, anterior and posterior trunk accelerations are related to forward leaning angular accelerations.

4.7 Findings

In this chapter, the findings of the statistical analysis of simulated normal and abnormal gait experiments can be summarised as follows. These findings lead to the proposals of the fall reduction algorithm stated in Chapter 5.

1. Normal gait trunk acceleration shows consistent periodical gait cycle pattern and peak-to-peak amplitude in every gait cycle, while abnormal gait trunk acceleration shows fluctuating and inconsistent gait cycle pattern and peak-to-peak amplitude in every gait cycle.

2. The mean value of trunk acceleration in abnormal gain for all ML direction, AP direction and VT direction is significantly greater than

those of normal gait.

3. Upper bound of trunk acceleration in normal gait does not overlap with lower bound of trunk acceleration in abnormal gait.

4. There is no significant difference between trunk acceleration of elderly and young adults.

5. Female test subjects have a barely higher mean value of trunk acceleration compared to that of male test subjects with the small difference being below 0.6g.

6. Two end results were observed in abnormal gait experiment. In the first, the test subject can recover from abnormal gait. For, the second, test subjects were not able to recover from abnormal gait and experienced near fall after a few cycles of abnormal gait.

CHAPTER 5

THE PROPOSALS OF FALL REDUCTION ALGORITHMS

5.1 Introduction

The statistical analysis of trunk acceleration data collected in both simulated normal gait and abnormal gait experiments in Chapter 4 showed that trunk acceleration data can be used to distinguish normal gait and abnormal gait. Once a user starts to experience abnormal gait that can be distinguished through trunk acceleration data, the user can be reminded to recover from abnormal gait. Thus, two fall reduction algorithms were proposed based on abnormal gait detection threshold and near fall detection threshold. These two fall reduction algorithms are named as universal fall reduction algorithm and individual fall reduction algorithm respectively. Universal fall reduction algorithm can be applied to all people regardless of their ages and genders while individual fall reduction algorithm is tailor made for each specific user. Universal fall reduction algorithm was inspired from the finding that upper bound of trunk acceleration in normal gait does not overlap with lower bound of trunk acceleration in abnormal gait (Figure 4.5) while individual fall reduction algorithm is inspired by the finding that the gait cycle duration and the trunk acceleration amplitude for every individual test subject are similar, but different from other test subjects. Lastly, the sensitivity or accuracy of both fall reduction algorithms are evaluated.

5.2 The proposal of universal fall reduction algorithm

Universal fall reduction algorithm is a threshold based algorithm. This algorithm would be appriopdrate for all people regardless of their ages and genders. This algorithm consists of two thresholds, namely universal abnormal gait detection threshold and universal near fall detection threshold. These thresholds are defined based on trunk acceleration data collected in simulated normal and abnormal gait experiments.

5.2.1 Universal abnormal gait detection threshold

The threshold is set based on statistical data collected in the simulated normal gait and abnormal gait experiments. First, collected trunk acceleration data $g_{i\in(1,\ldots,N)}(trunk)i$ in the simulated normal gait experiment was used to compute the mean value $\bar{x}$ and standard deviation δ by using Equation (5.1) and Equation (5.2).

$$\text{Mean value } \bar{x} = \sum_{i=1}^{\infty}(g_i)/n \tag{5.1}$$

$$\text{Standard deviation } \delta = \frac{\sqrt{\sum_{i=1}^{n}(g_i - \bar{x})^2}}{n-1} \tag{5.2}$$

Subsequently, confidence interval (CI) for mean can be computed using Equation (5.3),

$$99\%\ \text{CI} = \bar{x} \pm Z_c\,(\delta/\sqrt{n}) \tag{5.3}$$

where Z_c denotes the confidence level critical value for 99% confidence interval, i.e., 2.575. The usage of 99% of confidence interval instead of 95% of confidence interval is to have 1% of error instead of 5% of error to improve the data accuracy. Thus, 99% confidence interval for the mean value of upper bound (UB) and lower bound (LB) can be computed using Equation (5.4) and Equation (5.5),

$$UB_{99\%\ CI} = \bar{x} + 2.575(\delta/\sqrt{n}) \tag{5.4}$$

$$LB_{99\%\ CI} = \bar{x} - 2.575(\delta/\sqrt{n}) \tag{5.5}$$

The threshold level range will be between UB trunk acceleration of normal gait and LB trunk acceleration of abnormal gait. The threshold level is defined as the middle of the ranges in between 99% confidence interval for the mean of lower bound of trunk acceleration data collected in the simulated abnormal gait experiment $LB_{abnormal}$ and 99% confidence interval for the mean of upper bound of trunk acceleration data collected in the simulated normal gait experiment UB_{normal},

$$(LB_{abormal}) - \{(LB_{abormal}-UB_{normal})/2\} \tag{5.6}$$

From Equations (5.4-5.6), abnormal gait detection threshold can be rewritten as Equation (5.7),

$$(\{\bar{x} - 2.575(\delta/\sqrt{n})_{\ abormal}) -$$

$$\{(\left\{\bar{x} - 2.575\left(\frac{\delta}{\sqrt{n}}\right)\right\}_{abormal} - \{\bar{x} + 2.575(\delta/\sqrt{n})\}_{normal})/2\} \tag{5.7}$$

where $\bar{x}$ denotes the mean of the sample data calculated using Equation (5.1), δ denotes the standard deviation of the sampled data calculated using Equation (5.2) and n denotes the sample size of the data. The results of the universal abnormal gait detection threshold for three different directions are summarised in Table 5.1

Table 5.1: Universal abnormal gait detection threshold for three directions

Direction	**Trunk accelerations of normal gait**		**Trunk acceleratio ns of Abnormal gait**		**Threshold level ranges and threshold**
ML (Medio-lateral)	LB	0.46	LB	1.14	ML threshold level ranges: 0.56 < TH <1.14 ML Threshold: 1.14 – {(1.14-0.56)/2} = **0.85g**
	UB	0.56	UB	1.48	
AP (Anterior Posterior)	LB	0.40	LB	1.46	AP threshold level ranges: 0.51 < TH <1.46 AP Threshold: 1.46 – {(1.46-0.51)/2} = **0.98g**
	UB	0.51	UB	1.99	
VT (Vertical)	LB	1.60	LB	3.28	VT threshold level ranges: 1.69 < TH <3.28 VT Threshold: 3.28 – {(3.28-1.69)/2} = **2.48g**
	UB	1.69	UB	3.83	

Remarks:
1. The threshold level ranges are in between the UB trunk acceleration of normal gait and LB trunk acceleration of abnormal gait.
2. The threshold levels are defined in the middle of the ranges.

5.2.2 Universal near fall detection threshold

It was observed that some test subjects were able to recover from abnormal gait and back to normal gait when they exceeded the abnormal gait detection threshold (more details can be found in Section 4.4). Therefore, the detection of abnormal gait could not be claimed as near fall detection. As a result, a near fall detection threshold was also proposed.

In the simulated abnormal gait experiment, near fall condition will occur if the test subject continues to experience gait disorder after a period of time. Near fall condition can be observed when the safety belt that supports the test subject from fall is in tension. When the safety belt that supports the test subject from fall is in tension, the trunk acceleration will be recorded as maximum abnormal gait trunk acceleration value. This value is used to define as near fall threshold. Near fall threshold is the threshold when test subject experiences near fall condition. If this condition continues, the test subject will experienced fall.

The threshold value is defined based on 99% confidence interval for the mean of upper bound of trunk acceleration data collected in the simulated abnormal gait experiment $UB_{abnormal}$. A 99% confidence interval for the mean of upper bound is applied as this is the lowest value when the test subject experienced near fall gait. The near fall detection threshold value can be computed using Equation (5.8),

$$\left\{\bar{x} + 2.575\left(\frac{\delta}{\sqrt{n}}\right)\right\}_{abnormal} \tag{5.8}$$

where $\bar{x}$ denotes the mean of the sampled data, δ denotes the standard deviation of the sampled data and n denotes the sample size of the data. Table 5.2 shows the near fall threshold in ML, AP and VT directions based on Equation (5.8).

Table 5.2: Near fall gait detection threshold for three directions

Direction	**Threshold levels**
ML	ML threshold level: 1.48g TH ≥ 1.48
AP	AP Threshold level: 1.99g TH ≥ 1.99
VT	VT Threshold level: 3.83g TH ≥ 3.83

5.2.3 Classification of normal gait, abnormal gait and near fall gait

Universal abnormal gait detection and universal near fall detection thresholds were used to distinguish the following three different gaits:

1. Normal gait: Normal gait is classified if the trunk acceleration input value g_{in} is less than universal abnormal gait threshold, i.e., g_{in} < $(LB_{abormal}) - \{(LB_{abnormal} - UB_{normal})/2\}$. More precisely, Equation (5.9) is performed.

$$g < \left(\left\{\bar{x} - 2.575\left(\frac{\delta}{\sqrt{n}}\right)\right\}_{abormal}\right) -$$

$$\left\{\left(\left\{\bar{x} - 2.575\left(\frac{\frac{\sqrt{\sum_{i=1}^{n}(g_i - \bar{x})^2}}{n-1}}{\sqrt{n}}\right)\right\}_{abnormal} - \left\{\bar{x} + 2.575\left(\frac{\frac{\sqrt{\sum_{i=1}^{n}(g_i - \bar{x})^2}}{n-1}\delta}{\sqrt{n}}\right)\right\}_{normal}\right)/2\right\} \tag{5.9}$$

2. Abnormal gait: Abnormal gait is classified if the trunk acceleration input value g_{in} is equal or bigger than universal abnormal gait threshold but lesser than universal near fall detection threshold, i.e., where $LB_{abnormal} > g_{in} \geq [(LB_{abnormal}) - \{(LB_{abnormal}-UB_{normal})/2\}]$. More precisely, Equation (5.10) is performed.

$$\left\{\bar{x} - 2.575\left(\frac{\delta}{\sqrt{n}}\right)\right\}_{abnormal} > g \geq [(\left\{\bar{x} - 2.575\left(\frac{\delta}{\sqrt{n}}\right)\right\}_{abnormal}) -$$

$$\{(\left\{\bar{x} - 2.575\left(\frac{\frac{\sqrt{\sum_{i=1}^{n}(g_i - \bar{x})^2}}{n-1}}{\sqrt{n}}\right)\right\}_{abnormal} - \{\bar{x} + 2.575\left(\frac{\frac{\sqrt{\sum_{i=1}^{n}(g_i - \bar{x})^2}}{n-1}}{\sqrt{n}}\right)\}_{normal})/2\}]$$

(5.10)

3. Near fall gait: Near fall gait is classified as the trunk acceleration input value g_{in} being equal or greater than universal near fall detection threshold, i.e., $g_{in} \geq UB_{abnormal}$. More precisely, Equation (5.11) is performed.

$$g \geq \left\{\bar{x} + 2.575\left(\frac{\delta}{\sqrt{n}}\right)\right\}_{abnormal} \qquad (5.11)$$

5.2.4 Universal fall reduction algorithm

There exist three directions, i.e., ML, AP and VT directions. The universal abnormal gait detection threshold and the universal near fall detection threshold for these three directions can be found from Table 5.1 and Table 5.2 respectively. Equation (5.12) is performed to distinguish normal gait, abnormal gait and near fall gait based on three directions. To classify as abnormal or near fall, the trunk accelerations of all three directions (ML, AP and VT) of the test subjects must exceed the derived thresholds.

$$\begin{Bmatrix} normal\ gait:\ g(ML) < LBabormal(ML) - \left\{\dfrac{LBabormal - UBnormal}{2}\right\}(ML) \\ abnormal\ gait:\ LBabormal(ML) > g(ML) \geq LBabormal(ML) - \left\{\dfrac{LBabormal - UBnormal}{2}\right\}(ML) \\ near\ fall\ gait: g(ML) \geq UBabormal\ (ML) \end{Bmatrix}$$

and

$$\begin{Bmatrix} normal\ gait:\ g(AP) < LBabormal(AP) - \left\{\dfrac{LBabormal - UBnormal}{2}\right\}(AP) \\ abnormal\ gait:\ LBabormal(AP) > g(AP) \geq LBabormal(AP) - \left\{\dfrac{LBabormal - UBnormal}{2}\right\}(AP) \\ near\ fall\ gait: g(AP) \geq UBabormal\ (AP) \end{Bmatrix}$$

and

$$\begin{Bmatrix} normal\ gait:\ g(VT) < LBabormal(VT) - \left\{\dfrac{LBabormal - UBnormal}{2}\right\}(VT) \\ abnormal\ gait:\ LBabormal(VT) > g(VT) \geq LBabormal(VT) - \left\{\dfrac{LBabormal - UBnormal}{2}\right\}(VT) \\ near\ fall\ gait: g(VT) \geq UBabormal\ (VT) \end{Bmatrix}$$

(5.12)

Figure 5.1 shows the flow chart of universal fall reduction algorithm. The universal fall reduction algorithm developed using a mobile apps consists of the following steps:

1. Capture the trunk acceleration input value g_{in} using the tri-axial accelerometer.
2. Compare the trunk acceleration input value with pre-defined universal abnormal gait detection threshold and universal near fall detection threshold using Equation (5.12).
3. If all abnormal gait thresholds exceeded, send an abnormal gait alert message to both the user and the caregiver.
4. If all near fall gait thresholds exceed, send a near fall alert message to both the user and the caregiver.

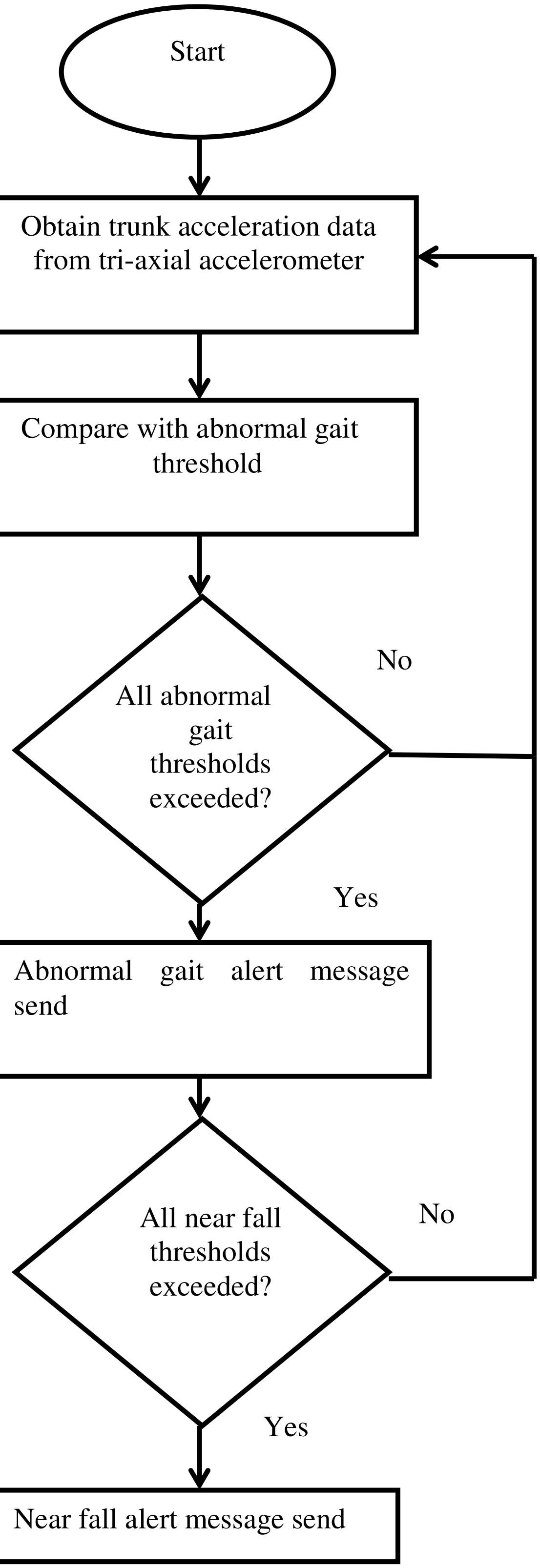


Figure 5.1: Flow chart of universal fall reduction algorithm

5.2.5 The recognition performance of universal fall reduction algorithm

5.2.5.1 Test subjects

A total of 144 test subjects were involved in the aforementioned simulated normal gait and abnormal gait experiments to define the universal abnormal gait detection threshold and the universal near fall detection threshold. A total of 74 young healthy subjects and 26 elderly healthy subjects participated in evaluating the recognition performance of the proposed universal fall reduction algorithm. These additional 100 test subjects were not involved in the experiments to define the universal abnormal gait detection threshold and the universal near fall detection threshold.

Each subject repeated the experiment twice to ensure the data collected is reliable. Informed consents were obtained from all subjects in advance. The young subjects consist of 40 males and 34 females with ages between 20 to 55 years old and their weights between 45kg to 75kg. Meanwhile, the elderly subjects consisted of 16 male and 10 female with ages between 56 to 66 years old and weights between 46kg to 69kg.

5.2.5.2 Experiment device and method

Universal fall reduction algorithm as shown in Figure 5.1 was constructed and implemented into an android based smartphone. The same simulated abnormal gait experiment method that was used to collect the trunk acceleration data for abnormal gait and near fall detection threshold was applied in the experiment. Instead of setting a tri-axial accelerometer at the waist of the test subject, a smartphone that contains an accelerometer was inserted into a tight-fit waist bag located at the waist of the test subject as shown in Figure 5.2.

Figure 5.2: Orientation of smart phone into a waist bag

5.2.5.3 Evaluation results

The performance evaluation results showed that pre-defined universal abnormal gait detection threshold can detect the abnormal gaits of 98 test subjects (out of 100 test subjects). The near fall detection threshold can identify near fall gait of 90 test subjects as shown in Figure 5.3. Two test subjects experienced near fall condition was only detected as abnormal gait. Furthermore, 10 test subjects who experienced near fall condition were able to recover from near fall situation and returned to normal gait. These 10 test subjects consist of six males and four females.

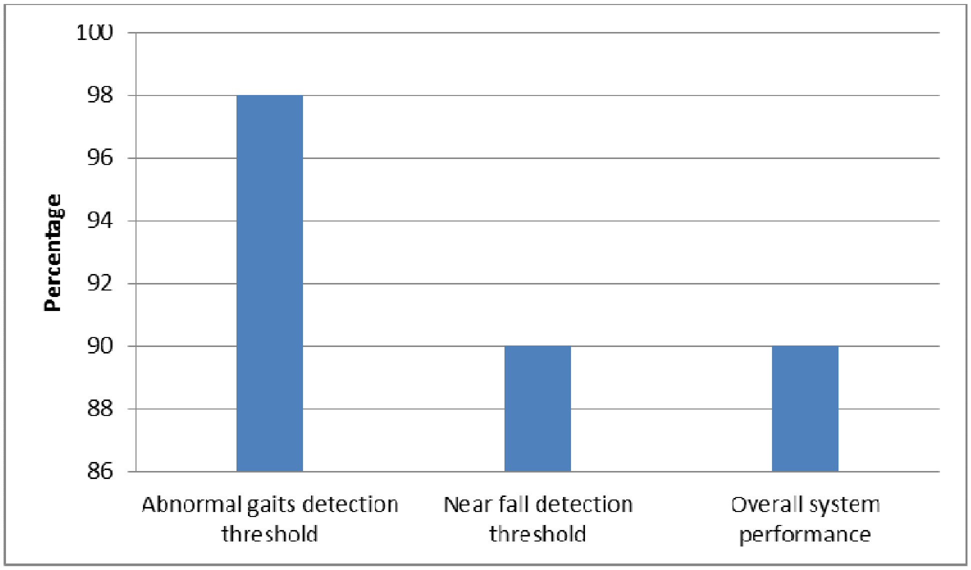


Figure 5.3: Summary of universal abnormal gait detection and near fall detection threshold evaluation result

5.2.5.4 Discussions

The detection rate for abnormal gait and near fall gait was 98% and 90% respectively. Since the universal fall reduction algorithm is based on the accuracy of both thresholds, therefore the overall performance of the universal fall reduction algorithm is 90%.

In the experiment to evaluate the performance of universal fall reduction algorithm, it was observed that a test subject who has better lower extremity strength and sensory-motor system was able to overcome balance disorder when experiencing abnormal gait and return to normal gait. In contrast, the test subject who has weaker lower extremity strength and sensory-motor system will experience near fall gait without experiencing abnormal gait.

Lower extremity strength and sensory-motor system are considered as random variables in the experiments. There are no specific subjects grouping for data collections by considering subjects' lower limb extremity strength, adequate sensory-movement system. In fact, there are diverse factors and situations of gait and balance disorder. It is believed that gait and balance disorders are the result of an interaction between environmental challenges and many deficits concerning mainly cognitive, neuromuscular or cardiovascular functions. Researchers have found that ageing and medical conditions are the causes of gait and balance disorder. Medical conditions associated with gait and balance disorder are affective disorder and psychiatric conditions, cardiovascular diseases, infectious and metabolic diseases, musculoskeletal disorders, neurologic disorders and sensory abnormalities (Alexander, 1996; Alexander & Goldberg, 2005; Moylan & Binder, 2007; Salzman, 2010; Sudarsky, 2001).

Forner-Cordero et al. (2003) reported that the ability to recover from abnormal gait depends on the physical condition of an individual. The physical condition can be classified as mechanical which can be a muscular force or joint ranges of motion, neurological which includes a muscular activation delay or sensory thresholds, and psychological which is the ability to adapt to new situations and self-perception of stability (Forner-Cordero et al., 2003). The finding of this research is consistent with the finding reported by Forner-Cordero et al. (2003).

5.3 The Proposal of individual fall reduction algorithm

The gait cycle duration and the trunk acceleration amplitude for every individual test subject were similar, but different from other test subjects. Thus, each individual may have unique abnormal gait detection threshold and near fall detection threshold. The 90% accuracy of the proposed universal fall reduction algorithm also suggested that the universal fall reduction algorithm may not apply to certain people. This is because test subject who has better lower extremity strength is able to overcome balance disorder when experiencing abnormal gait while the test subject who has weaker lower extremity strength will experience near fall gait without experiencing abnormal gait.

In addition, test subjects may have different chronological age and biological age. Chronological age is commonly defined as the age of a person counted from the date the person was born. Based on research in biological age, chronological age may not be a reliable indicator of the body's rate of decline or physiological breakdown. Given the number of cellular and systemic changes that accompany the ageing process, it is believed that such changes could be quantified through the identification and measurement of biomarkers of ageing (Levine, 2013).

Karasik et al. (2005) reported that tissues age at different rates, humans become increasingly different from one another with age and eventually, chronological age will fail to provide an accurate indicator of the ageing process. People who have younger tissues and organs age might be deemed biologically younger, and people with poor tissues and organs functions are categorised as biologically older. Biological age may help in identifying individuals at risk for age-related disorders, serving as a measure of relative fitness, and predicting disability in later life and mortality independent of chronological age (Mitnitski, 2013; Uttley & Crawford, 1994). According to Horak (2006), balance control involve various body physiological systems. Pathology or sub-clinical constraints can affect the functionality of the physiological systems. Functionality impairment of these systems will result in various context-specific instabilities. Therefore, the understanding of multiple mechanisms underlying postural control and the functions of physiological systems that will affect balance control are important in the study of human gait.

Thus, the aforementioned reasons and results have motivated the proposal of individual fall reduction algorithm based on individual abnormal gait detection threshold and individual near fall detection threshold. These two thresholds are unique to each individual. These thresholds are defined based on trunk acceleration data collected in simulated normal and abnormal gait experiments.

5.3.1 Classification of normal gait, abnormal gait and near fall gait

Individual abnormal gait detection and individual near fall detection thresholds were used to distinguish the following three different gaits where the thresholds are set based on statistical data collected on each individual in the simulated normal gait and abnormal gait experiments. Notice that individual abnormal gait detection threshold, $a(\text{normal})_{\text{Max}}$, is the maximum individual trunk acceleration value captured in the simulated normal gait experiment.

1. Normal gait: Normal gait is classified if the trunk acceleration input value g_{in} is less than individual abnormal gait threshold, i.e., $g_{in} < a(\text{normal})_{\text{Max}}$.
2. Abnormal gait: Abormal gait is classified if the trunk acceleration input value g_{in} is equal to or more than individual abnormal gait threshold (but less than the near fall gait threshold that will be defined later), i.e., $g_{in} \geq a(\text{normal})_{\text{Max}}$.
3. Near fall gait: Near fall constant is defined by Equation (5.13) based on the data collected in the simulated normal gait and abnormal gait experiments.

$$CI_{LB}(\text{abnormal})/CI_{UB}\ (\text{normal}) \qquad (5.13)$$

where CI_{UB}(normal) and CI_{LB} (abnormal) denote 99% confident interval for the mean value of upper bound and lower bound trunk acceleration data collected in the simulated normal gait and abnormal gait experiments respectively. CI_{LB} (abnormal) and CI_{UB} (normal) can be obtained from statistical analysis result listed in Table 4.1. Table 5.3 shows the near fall constant in ML, AP and VT directions. The near fall constants in ML, AP and VT directions are 2.03, 2.86 and 1.94 respectively. Finally, the individual near fall detection threshold can be obtained by Equation (5.14), Equation (5.15) and Equation (5.16),

$$NFTA_{ML} = 2.03(NGTA_{ML(Max)}) \tag{5.14}$$

$$NFTA_{AP} = 2.86(NGTA_{AP(Max)}) \tag{5.15}$$

$$NFTA_{VT} = 1.94(NGTA_{VT(Max)}) \tag{5.16}$$

where NFTA denotes near fall trunk acceleration value and $NGTA_{(Max)}$ denotes maximum normal gait trunk acceleration value.

Table 5.3: Near fall constants in ML, AP and VT directions

Directions	ML	AP	VT
CI_{LB}(abnormal)[1]/CI_{UB} (normal)[2]	2.03	2.86	1.94

Remarks:

1. CI_{LB} =99% Confidence Interval for Mean of Lower Bound

2. CI_{UB} = 99% Confidence Interval for Mean of Upper Bound

Near fall gait is classified if the trunk acceleration input value g_{in} is equal or more than individual near fall gait threshold, i.e., $g_{in} \geq$ NFTA.

5.3.2 Individual fall reduction algorithm

Equation (5.17) is performed to distinguish normal gait, abnormal gait and near fall gait based on three directions. To classify as abnormal or near fall, the trunk accelerations of all three directions (ML, AP and VT) of the test subjects in must be exceed the derived thresholds.

$$\begin{Bmatrix} normal\ gait\text{:}\ \ g(ML) < a(normal)ML(\max) \\ abnormal\ gait\text{:}\ \ a(NFTA)ML > g(ML) > a(normal)ML(\max) \\ near\ fall\ gait\text{:}\ g(ML) \geq a(NFTA)ML \end{Bmatrix}$$

and

$$\begin{Bmatrix} normal\ gait\text{:}\ \ g(AP) < a(normal)ML(\max) \\ abnormal\ gait\text{:}\ \ a(NFTA)AP > g(AP) > a(normal)AP(\max) \\ near\ fall\ gait\text{:}\ g(AP) \geq a(NFTA)AP \end{Bmatrix}$$

and

$$\begin{Bmatrix} normal\ gait\text{:}\ \ g(VT) < a(normal)VT(\max) \\ abnormal\ gait\text{:}\ \ a(NFTA)VT > g(VT) > a(normal)VT(\max) \\ near\ fall\ gait\text{:}\ g(VT) \geq a(NFTA)VT \end{Bmatrix} \tag{5.17}$$

Figure 5.4 shows the flow chart of individual fall reduction algorithm. For a repeated user, the individual fall reduction algorithm developed using a mobile apps consists of the following steps:

1. Capture the trunk acceleration input value g_{in} using the tri-axial accelerometer in ML, AP and VT directions.
2. Compare the trunk acceleration input value with pre-defined individual abnormal gait detection threshold and individual near fall detection threshold.
3. If abnormal gait is detected, send an abnormal gait alert message to both the user and the caregiver.
4. If near fall gait is detected, send a near fall alert message to both the user and the caregiver.

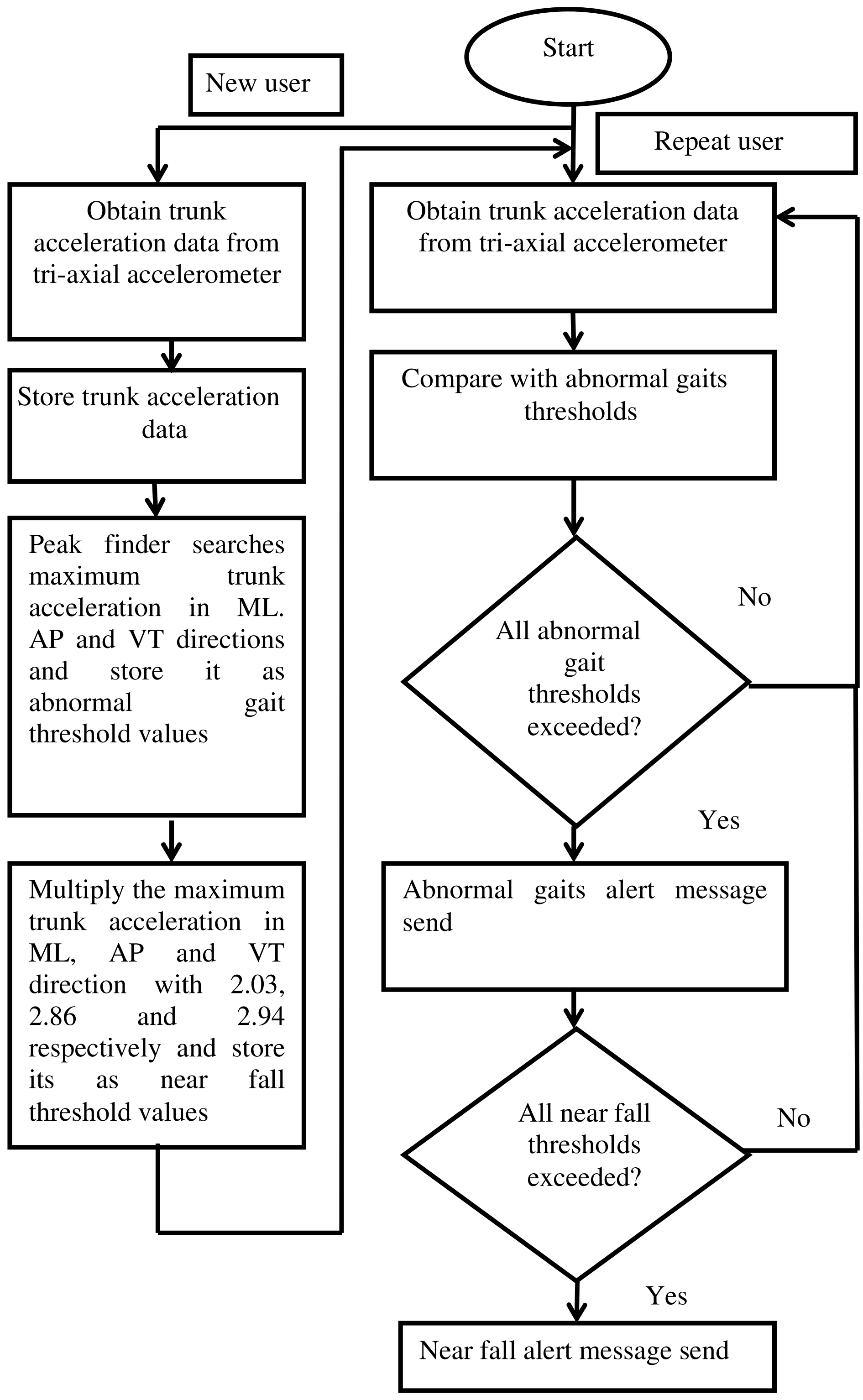


Figure 5.4: Flow chart of individual fall reduction algorithm

For a new user, experiments need to be performed to identify the individual abnormal gait threshold and individual near fall threshold as explained earlier.

5.3.3 The recognition performance of individual fall reduction algorithm

5.3.3.1 Test subjects and experiment devices

The same test subjects and same experiment setup described in Section 5.2.5 were employed in evaluating the recognition performance of the proposed individual fall reduction algorithm. The main differences in evaluating the proposed universal fall reduction algorithm and individual fall reduction algorithm are listed as follows:

1. Different proposed algorithms were implemented and installed into an android based smartphone.
2. The training set of the proposed universal fall reduction algorithm consists of 144 test subjects while the verification or validation set of the proposed universal fall reduction algorithm were examined using of 100 test subjects that are different from the training set to evaluate the effectiveness of universal abnormal gait detection threshold and universal near fall detection threshold on all people.
3. The training set and validation set of the proposed individual fall reduction algorithm consists of 100 similar test subjects to check the effectiveness of unique individual abnormal gait detection threshold and individual near fall detection threshold.

5.3.3.2 Experiment procedure

The overall experiment in evaluating the accuracy of the proposed individual fall reduction algorithm consists the following steps:

1. Test subjects were requested to walk with their normal gait on 10 meters flat and dry floor. The process was repeated two times to ensure the test subjects have consistent gaits.
2. Test subjects were instructed to walk on the treadmill for 20 minutes to get used to the treadmill. The starting belt-conveyer moving speed was set to 1.1m/s (i.e., 4 km/h) as this speed was comfortable for all of the volunteers during the trial.
3. Test subjects were asked to activate the mobile apps installed on a smartphone inserted into a tight-fit waist bag located at the waist of the test subjects.
4. Test subjects were asked to avoid stepping on 10 mm round stickers randomly pasted on the treadmill to create abnormal gait condition.
5. Alert message was sent if the trunk acceleration input value is greater or equal to the pre-defined thresholds.
6. Experiment will be stopped when the safety belt that supports the subjects from fall is in tension.

5.4 Individual fall reduction algorithm evaluation result

It was found that, the individual fall reduction threshold can detect all abnormal gaits and near fall condition of all test subjects as shown Figure 5.5. The individual fall reduction software can classify the incoming trunk acceleration into a normal gait, abnormal and near fall gait. An alert was successfully sent to the care giver when abnormal, and near fall gait was detected. The individual fall reduction algorithm has achieved 100% accuracy in the experiment to verify the individual fall reduction software performance.

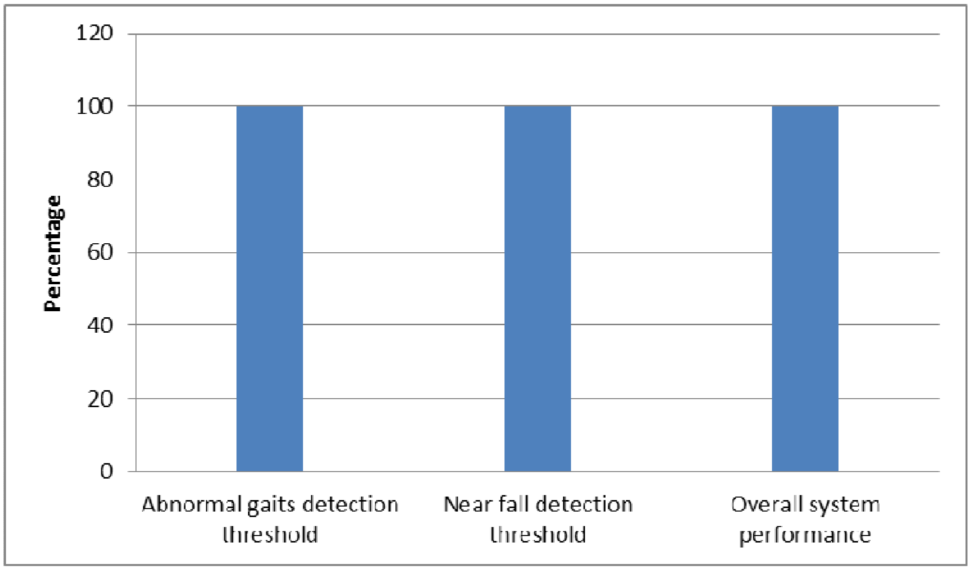


Figure 5.5: Summary of individual abnormal gait detection and near fall detection threshold evaluation result

5.5 Summary

Two types of the fall reduction algorithms were created. Universal fall reduction algorithm consists of universal abnormal gait detection threshold and universal near fall detection threshold. These thresholds were defined based on the statistical analysis result of simulated normal and abnormal gait experiments. Individual fall reduction algorithm consists of individual abnormal gait detection threshold and individual near fall detection threshold. Individual abnormal gait detection threshold was obtained by carrying simulated normal gait experiment. Individual near fall detection threshold defined based on the multiplication of abnormal gait detection threshold with near fall constant obtained according to the statistical calculation result proposed in section 5.5.3. These thresholds are unique for every individual.

Figure 5.6 summarised the evaluation outcomes of universal fall reduction algorithm and individual fall reduction algorithm. Universal fall reduction algorithm has achieved 90% accuracy, and individual fall reduction algorithm has achieved 100% accuracy.

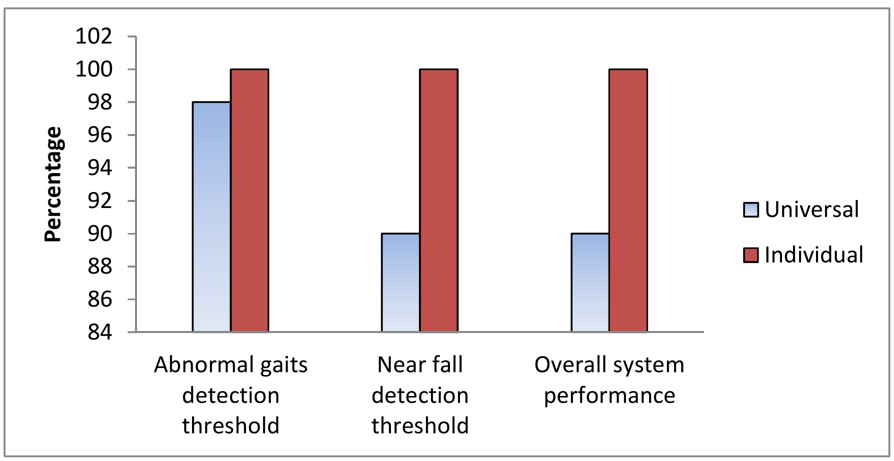


Figure 5.6: Universal and individual abnormal gait detection threshold, near fall detection threshold, overall universal and individual fall reduction algorithm performance evaluation result

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of research outcomes

This chapter concludes the research contributions and proposes future research direction. It is hypothesized that dynamic balance disorder during human locomotion will induce high trunk acceleration that will cause abnormal gait and eventually may result in falls. Quantitative analysis results have proved that it is possible to classify normal and abnormal gait based on the peak value of trunk acceleration. Threshold-based universal and individual fall reduction algorithms were created, and the reliability of these algorithms was evaluated. The outcomes of the research based on the research objectives can be concluded as below:

1. Normal gait trunk acceleration shows a consistent periodical gait cycle pattern and peak-to-peak amplitude in every gait cycle, while temporal profiles on for abnormal gaits experiment shows fluctuating and inconsistent trunk acceleration in an abnormal gait.
2. The mean values of abnormal trunk acceleration in all ML direction, AP direction and VT direction are significantly greater than normal gait.
3. Upper bound normal gait trunk acceleration does not overlap with lower bound abnormal gait trunk acceleration.
4. There is no significant difference between trunk acceleration of old and young test subjects.

5. Female test subjects have barely higher mean trunk acceleration value than male test subjects, with a small difference of below 0.6g.
6. Two conditions were observed in abnormal gait experiment. In the first condition, the test subject can recover from abnormal gait. In the second condition, volunteers were not able to recover from abnormal gait and experienced near fall after few cycle of abnormal gaits.
7. Two new gait experiment methods were introduced in this research. The first experiment method is simulated normal gait experiment and the second experiment method is simulated abnormal gait experiment. Simulated normal gait experiment is designed to capture trunk acceleration in the daily steady gait of the test subjects, while simulated abnormal gait experiment is designed to capture unstable abnormal gait of the test subjects.
8. The reliability of using a wireless accelerometer to capture trunk acceleration in normal gait and abnormal gait experiments were confirmed by repeating the simulated gait experiment on the same test subjects. It was found that same test subject demonstrated similar trunk acceleration pattern when the experiment was repeated twice. Also, the duration of the gait cycle and the trunk acceleration amplitude for every individual test subject is similar, but it is different from others. This has provided a remarkable evidence of the reliability of using a wireless tri-axial accelerometer to capture trunk acceleration in normal gait and abnormal gait.
9. Simulated normal gait and abnormal gait experiment results have revealed that there is a significant correlation between human trunk

acceleration, abnormal gait, and near fall. Statistical analysis result on trunk acceleration in normal and abnormal gaits has found that the trunk acceleration in normal gait and abnormal gait is different. Abnormal gait is an unstable gait that will cause in high trunk acceleration. The body is losing balance, and the test subjects need to move their upper and lower limbs to recover the unbalance body posture in abnormal gait back to normal gait (stable gait). This has caused high trunk acceleration in abnormal gait. The average trunk accelerations in abnormal gait that may lead to falling in mediolateral, anterior-posterior and vertical directions are 257%, 376%, and 217% larger than those of a normal gait respectively.

10. Two threshold based fall reduction algorithms were proposed in this research. The first fall reduction algorithm is universal fall reduction algorithm and second fall reduction algorithm is individual fall reduction algorithm:

    (a) Universal fall reduction algorithm consists of universal abnormal gait detection threshold and universal near fall detection threshold. The thresholds are defined according to the statistical calculation result of 144 test subjects obtained in simulated normal and abnormal experiments. Universal abnormal gait detection threshold value for ML, AP and VT directions are 0.85g, 0.98g and 2.48g respectively. Universal near fall detection thresholds for ML, AP and VT are 1.14g, 1.46 and 3.28g respectively. The same thresholds can be applied to all people regardless of age and gender.

(b) Individual fall reduction algorithm consists of individual abnormal gait detection threshold and individual near fall detection threshold. Individual abnormal gait detection threshold is obtained by carrying simulated normal and abnormal gait experiments. The threshold is unique for every individual. Individual near fall detection threshold is obtained by multiplying individual abnormal gait detection threshold with near fall constant. Near fall constant is obtained according to the statistical calculation result of test subjects in simulated normal and abnormal experiments. The near fall constants in ML, AP and VT directions are 2.03, 2.86 and 1.94 respectively. The threshold is unique for every individual.

11. Android-based software that based on the proposed algorithms have been evaluated and below are the evaluation results:

(a) Universal fall reduction algorithm was able to detect 98% of abnormal gait and 90% of near fall gait.

(b) Individual fall reduction algorithm was able to detect 100% of abnormal and near fall gaits.

Fall detection evaluation results have shown that it is possible to have a universal threshold with 90% sensitivity, but some test subjects can recover from abnormal gait or near fall gait (10%). This implies that individual may has unique threshold as the result of different lower extremity strength. Therefore, a self-learning threshold algorithm is proposed. The verification result has shown that individual fall reduction algorithm is more reliable and achieved 100% detection.

6.2 Future work

Pathological change in the body may affect the experiment result (An et al., 2017 and Barr et al., 2017). As such, current study only involved healthy subjects without gait disturbance. Studies have shown that, diseases could result in gait disorder. Normal pressure hydrocephalus and Parkinson's disease cause gait disorder (Stolze et al., 2011) and gait disturbance is observed in patients with Alzheimer's disease (O'keeffe et al., 1996). It is proposed to extend the current study of simulated normal and abnormal gaits using individual fall reduction algorithm proposed in this research to investigate the correlation between abnormal gaits with diseases. Besides, the finding of the proposed work could be used to monitor the health condition of the patient. Also, the study outcomes could also be used to develop an early detection of some diseases such as Parkinson's disease.

Balance control of ageing people degenerates (David et al., 1990 ; Winter et al., 1990) causing gait disorder (Ferrandze et al., 1988; Hageman and Blanke, 1986; Winter et al., 1990; Kressig et al., 2004). The proposed individual fall detection algorithm in this research can be used to monitor the condition of elderly impairment such as balance control ability and sensory-motor functionality. As this algorithm was developed based on control environment, it is proposed to carry in house experiment to verify the reliability of the algorithm for elderly impairment monitoring purpose.

According to Horak (2006), one of the factors that cause abnormal gait was due to the damage in any of the underlying physiological systems. Current study has revealed that there is a significant different on trunk acceleration in normal and abnormal gaits. Abnormal gait will cause in high trunk acceleration. Therefore, it is proposed to carry out a study to find out the possibility of applying fall reduction algorithm in gait rehabilitation. The patients that have gait impairment can monitor their gait stability by using the new developed individual fall reduction system. Consistent trunk acceleration amplitude and periodic gait cycle can be used as the indicators of gait stability.

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