NAIST-IS-DD1261026

Doctoral Dissertation

Application of Wearable Inertial Sensor in Clinical Practice

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September 18, 2013

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Graduate School of Information Science
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A Doctoral Dissertation
submitted to Graduate School of Information Science,
Nara Institute of Science and Technology
in partial fulfillment of the requirements for the degree of
Doctor of ENGINEERING

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Application of Wearable Inertial Sensor in Clinical Practice*

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Abstract

This study reports the quantitative classification of falling risk among elderly using the wearable inertial sensors, which combines accelerometer and gyrosensors devices, applied during standard physical assessment test; Timed Up and Go(TUG) test. The total time duration to complete the whole experiment were used as threshold to categorize the 38 subjects into two groups; as low fall risk (LFR) and high fall risk (HFR). During the experiment, one sensor was attached at the subject's waist dorsally. The acceleration and angular velocity signals in three directions were extracted using the sensors, during the test. The analysis then divided the whole test into phases: sit-bend, bend-stand, walking, turning, stand-bend, and bend-sit. Comparisons between the two groups using time parameters along with RMS value, amplitude and other parameters that was analysed from the extracted signal revealed the activities in each phase.

Using obtained parameters, we demonstrate classification process using k-nn for dual parameters classification, and multivariate analysis; PCA, LDA and random forest analysis for classification using multiparameters. In general, our study improves the classification using multi parameters in phases, providing movement information to the therapist by harnessing the quantitative information from the parameters. This is an improved method in evaluating fall risk, which promises benefits in terms of improvement of elderly Quality of Life(QOL).

Keywords:

falls, gait, wearable inertial sensor, classification, standard physical assessment

*Doctoral Dissertation, Department of Bioinformatics and Genomics, Graduate School of Information Science, Nara Institute of Science and Technology, NAIST-IS-DD1261026, September 18, 2013.

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Chapter 1

Introduction

The Prophet (pbuh) said: ”If a young man honors an elderly on account of his age, Allah appoints someone to honor him in his old age.”

At-Tirmidhi

This dissertation summarizes the author’s research experience and results achieved in applying of wearable inertial sensors in clinical analysis. The capability of the wearable inertial sensors to extract and provides parameters of subject’s dynamic movement were encouraged this research. This project also attempt to classify the elderly subject into two groups in determining the fall risk among elderly. This chapter describes the general background, the research problem and explains what is to be expected from the rest of the dissertation.

A standard test for physical activity assessment, which had been widely used by therapists all over the world, called TUG test was reported by [1]. This test has been extensively used to asses balance and mobility in elderly [2–4]. The test is considered simple because it uses total test time as a threshold in the evaluation of fall risk in the elderly. [5] suggested using 13.5 seconds duration to complete the whole test as the threshold to classify fallers and non-fallers. [6, 7] claimed that the sensitivity of the current approach depends on subjective judgement and the experience of the therapist. They suggested that using the wearable inertial sensors to classify the fall risk among the elderly will avoid the inconsistent results. In recent studies, researchers used three wearable inertial sensors to determine the phase transition, which were attached at the waist dorsally and also at both right and left thighs [6–8]. An alternative approach was developed by [9] to identify basic movements from the signals obtained from a single, waist-mounted triaxial accelerometer. Their study suggested dividing the movement into activities: falls, and walking transition between postural orientations and rest. The postural orientations during rest were classified as sitting, standing, or lying. In this study, a wearable inertial sensor attached at the waist dorsally was used for determining phase transitions and extracting phase activity during the TUG test. To circumvent the motions artifacts, the sensor must be securely attached to the waist. Accordingly, the sensor was slotted in a belt that was attached to the waist.The wearable inertial sensor is a combination of an accelerometer and gyrosensors that extract 3-dimensional acceleration signals and also 3-dimensional angular velocity signals. Use of three attached sensors would restrain the subject, therefore a new system was designed to be more easily handled by therapists. Tight fitting sensors need to be attached to the thighs in order to ensure they will not move around during the test. As a result, therapists could require less time to set up the sensors. In addition, it would be easier to handle 6 signals using a sensor instead of 18 signals from 3 sensors. Furthermore, the complexity of synchronization between sensors could be avoid.

Focusing only on time parameters and ignoring all activity involved in the test without separating the performance of the subject into phases, limits the evaluation possibilities. This study aims to show that quantitative analysis using the wearable inertial sensor attached only at the waist dorsally could classify falling risk among the elderly not only with a single parameter, but with multi-parameters simultaneously.

1.1. Background and Motivation

Total Japan's population as per calculated until October 2010 is estimated to be about 128 millions comprises of 29 millions people are elderly; persons 65 years and above. They represented 23% of the Japan's population which estimated about one in every five Japanese are elderly.

Table 1.1: Rank is the order of 24 countries listed, from longest to the shortest life expectancy. Source: WHO, "The World Health Report 2011"

Country	Male	Rank	Female	Rank	Both	Rank
Brazil	70	11	77	10	73	11
Italy	79	3	84	3	82	2
Canada	79	3	83	4	81	3
Netherlands	78	4	83	4	81	3
USA	76	6	81	6	79	5
Norway	79	3	83	4	81	3
China	72	9	76	11	74	10
Portugal	76	6	82	5	79	5
India	63	18	66	21	65	19
Russian	62	19	74	13	68	16
Japan	**80**	**2**	**86**	**1**	**83**	**1**
Spain	78	4	85	2	82	2
Korea	77	5	83	4	80	4
Sweden	79	3	83	4	81	3
Malaysia	71	10	76	11	73	11
Switzerland	80	2	84	3	82	2
Singapore	79	3	84	3	82	2
UK	78	4	82	5	80	4
Pakistan	62	19	64	23	63	21
Australia	80	2	84	3	82	2
Finland	77	5	83	4	80	4
New Zealand	79	3	83	4	81	3
France	78	4	85	2	81	3
Germany	78	4	83	4	80	4

Wealth and Health Organization (WHO) reported by year 2009, Japan is in the first ranking who has longest life expectancy as shown in Table 1.1. While, Figure 1.1 shows the trends and future estimation of life expectancy from year 1955 until year 2055 in Japan. By year 2009, the average life expectancy in Japan for male is 80 years old and 86 years old for female which scores the second and the first ranking respectively in Table 1. For both male and female, Japan again scores the first ranking with average life expectancy in elderly is 83 years old.

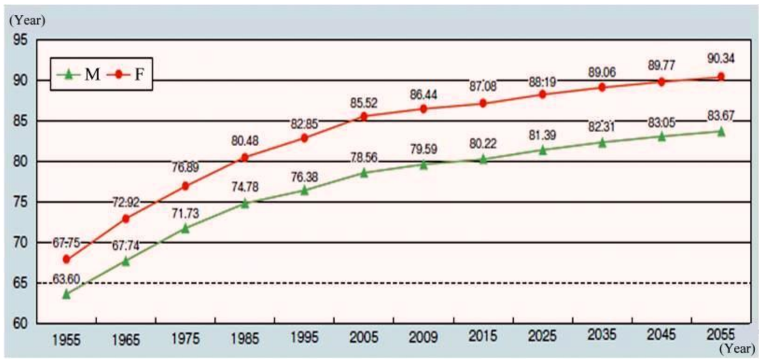


Figure 1.1: Trends and future estimation of life and expectancy.(Figure adapted from `http://www.mhlw.go.jp/`)

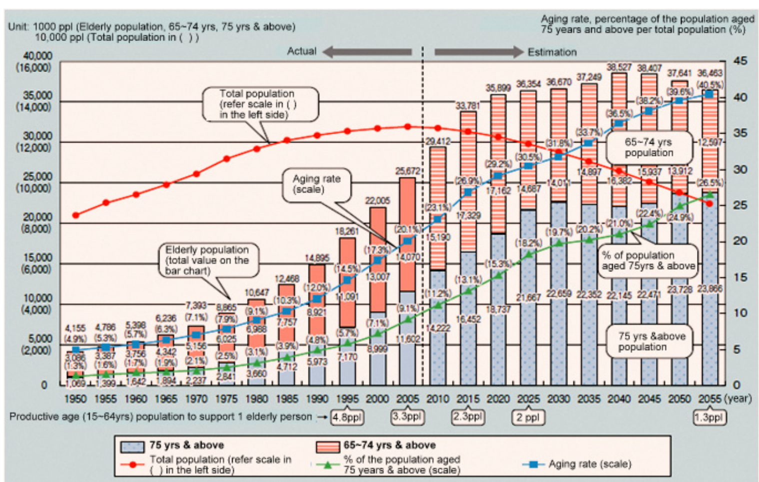


Figure 1.2: Elderly ageing trends and future estimation.(Figure adapted from `http://www.mhlw.go.jp/`)

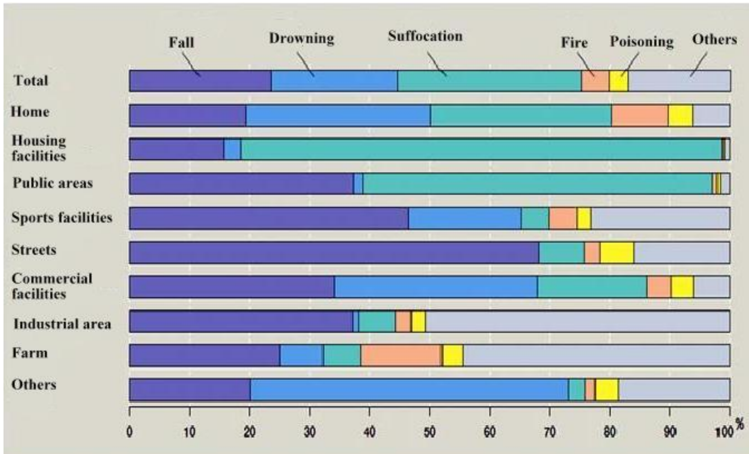


Figure 1.3: Percent distribution of accidental deaths due to causes other than traffic accidents.(Figure adapted from `http://www.mhlw.go.jp/`)

It is expected that the average life expectancy in male and female will increasing above 20% between years 1955 and 2055. Figure 1.2 shows the Elderly Ageing Trends and Future Estimation from year 1950 to year 2055. As a result from life expectancy estimation graph, the ageing trend in elderly also increasing year by year. It is estimated that there will be one in two Japanese are elderly by year 2055. Hence the welfare healthcare are expected to expand significantly in the future for continued improvement of elderly Quality of Life(QOL).

Figure 1.3 shows the percent distribution of accidental deaths due to causes other than traffic accident by type of accident and by type of occurrences. As a summary the main caused of accident at home are by suffocation and drowning. While in public area the main caused are the suffocation and falling in street or public area.

Every year, almost 30% of elderly falls worldwide and most of the case are unwitnessed. Falls leads to deterioration in health and physical activities; physiological distress, pain that was caused by the injuries, impairment or imbalance gait, fear of repeated fall and deterioration in QOL. These problems sometimes caused elderly becomes immobility, bedridden and sometime caused death. Realizing the fall are major problems among elderly, prevention of falls and injuries has been focused among researchers.

Subsequently, what are required in preventing the falls among elderly? The improvement of the fall risk screening among elderly are required to identify whether they are have the risk to fall for further analysis. The collected information then used in implementing the specific and targeted risk reduction strategies for subjects at high risk of falls injury. The elderly then need to report for investigation and monitoring the progress and condition.

In detecting and classifying fall risk among elderly, various method of physical assessment tools has being developed such as diaries, questionnaires and surveys; which are inexpensive tools. However these method is relies on individual observation and interpretation. The subjective decision judges by individual will leads to inconsistent result. Some standard assessment also had being developed such as Timed Up and Go test(TUG test), Four Square Step Test (FSST), 10 meters walking and others. These standard test verify patient's motion and movement with developed standard lay out. Therapist will using stopwatch to measure the duration taken by patients to complete the test. Patient with fall risk or not will judge using some time duration threshold. These method also leads to subjective individual observation by therapist.

To overcome this problem, researchers developed a new objective method using force plate and also 3-Dimensional motion capture system such as VICON. The force plate or force platform measures the ground reaction forces that is generated by body whether standing still or moving across the plate. It quantify balance, gait and others parameters of human body biomehcanics. The 3-Dimensional motion capture system records the movement of objects or people passing through the set-up multiple cameras. This system could provide and accurate data, however capture system cost of the software, equipment and personnel required are very expensive. Furthermore, it require specific space for it to operate in, depending on camera field of view or magnetic distortion or immobile.

To examine the fall risk, it is necessary to enable a quantitative evaluation in a simple, compact, mobile and more sensitive for a clinical test. Therefore, this study aim to show that a wearable inertial sensors can be used to objectively quantify and provide a quantitative evaluation of falling risk using accelerometers and gyrosensors applying to some standard physical test, TUG test and FSST.

In this dissertation, we present the application of wearable inertial sensors in clinical practise. The combination of accelerometer and gyrosensors devices, applied during some standard physical in classifying the fall risk among elderly.

1.2. Research contribution

Falls among the elderly have become a major concern with almost 30% of those aged 65 and above falling each year [4, 10–12], in most cases unwitnessed. Falls lead to deterioration of health and physical activities. These problems cause elderly people to become immobile and sometimes bedridden. Since falls are a major problem among the elderly, prevention of falls and related injuries has been a focus among researchers. Early studies utilized subjective methods to study this issue, such as questionnaires and surveys leading to inconsistent results as they depend on individual observation and interpretation. Various standard test assessments for physical activities, such as TUG test, FSST, step test, and walking test, also depend on intuitive judgement and experience of a therapist. On the other hand, force plate and 3-Dimensional motion capture system, such as VICON, are objective methods that were introduced to evaluate the fall risk [13, 14]. Nonetheless, objective methods are costly and their evaluation can only be carried out in limited spaces. Apparently, there is a need to evaluate falling risk quantitatively using a low cost, simple, compact, and more sensitive method for a clinical test. Therefore, this study aims to show that a wearable inertial sensors can be used to objectively quantify and provide a quantitative evaluation of falling risk using accelerometers and gyroscopes applying to timed up and go test (TUG), and harnessing the quantitative information well beyond simply the time taken to perform the test.

Our research intend to focus on these scopes of studies:

1. Using wearable inertial sensor to extract acceleration signals and angular velocity signals taken during the tests

2. Divide the whole test into phases: sit-stand, walk, turning *etc.* in order to obtain parameters for each phases for low fall-risk(LFR) and high fall-risk(HFR) using TUG test.

3. Choose the most important parameters from the obtained parameters that influenced the most in predicting and classifying elderly into LFR and HFR,

and harnessing the quantitative information for subject's condition interpretation.

1.3. Dissertation Layout

This dissertation is organized as follows:

- **Chapter One** gives the overview of elderly population and statistic worldwide, mainly in Japan. This chapter also explain the introduction of the fall risk and the background and motivation of the research. The research contributions and the dissertation layout are also given in this chapter.

- **Chapter Two** covers the method used in the research. This section illustrate how the experiment done, how many subjects were participated and how analysis were applied in this research. Some related works and background are also given to briefly explain the investigated field. It gives the overview of the wearable inertial sensors, the standard physical assessments; timed up and go test used in this research. Related works of other authors were also presented in this chapter. The chapter provides the the foundation of the algorithm and analysis of the classification technique that are necessary for the research.

- **Chapter Three** presents the results of the project. In this section, all gathered parameters extracted form acceleration signal, angular velocity signal and angular signal in phases were listed in a table. This chapter also covers the classification of the subjects into groups using the significant parameter obtained from analysis.

- **Chapter Four** The overall project is rationalized and concluded in this chapter. Some issues regarding the results obtained discussed and proposals of future works are also suggested in this chapter.

- **Chapter Five** summarizes the work done in our research.

Chapter 2

Method

2.1. Introduction

> The prophet saw said: "Give due respect and regard to your children and decorate them with the best of manners".
>
> Abu Daud

The timed up and go test (TUG) is a clinical tool that is widely used to assess functional balance and mobility, primarily in older adults. Traditionally, the test is scored by manually recording the time taken to complete the whole test, started when subject start to rise out of a standardized chair, walk three meters, turn around, walk back, turn and sit back down in the chair. For research purposes, the TUG test has been modified in a number of ways to enable the tester to examine the component parts of the test individually for example [15], or by adding cognitive [16] or additional physical challenges [17] to the test. This study aimed in using the body-worn sensor technology to increase the scope for harnessing quantitative information from the TUG, well beyond simply the time taken to perform the test. Wireless inertial sensors worn by the participant during the TUG can provide large volumes of angular velocity and acceleration data, which can be used to compute a variety of gait and movement parameters, depending on which body part the sensor is attached to. This chapter discusses the basic principle of the project background involving the wearable inertial sensor used, the acceleration signal,angular velocity signal in normal elderly, how the experiment and analysis were carried out in this study, and also includes why this study is obligatory. The algorithm used in analysing the parameters extracted and obtained were also outlined in this chapter.

2.2. Wearable Inertial Sensors

An important indicator of fall risk in the elderly is balance or stability control posture while standing still or walking [20]. Motion is described by displacement, velocity, and acceleration. Trunk tilt reflects the angle between axes. Trunk tilt, which corresponds to the angle and the acceleration factor, was considered for physical assessment of the elderly in this study. For this, a wearable inertial sensor was used [21, 22]. According to [22], the wearable inertial sensor can be divided into 4 parts: sensor, amplifier, transmitter, and data processing part. The sensor part was installed with a combination of 3D (anteroposterior, mediolateral, and vertical axes) accelerometers (MMA7260Q Freescale semiconductor inc. Texas USA) and three 1D gyro sensors (ENC-03R, Murata , Kyoto, Japan & XV-3500CB, Miyazaki Epson Corp,Nagano,Japan) for roll, yaw, and pitch axes. The measured signal was then amplified using an amplifier. The accelerometer sensor could measures 3 axes of acceleration with a sensitivity of ±2g for a sensitivity of 600mv/g, and ±4g for a sensitivity 400mv/g. As the gyrosensor could measure only one axis, three gyrosensors were required with sensitivity of 0.67 mv/deg/s to measure three axes. In the data processing part, amplified signals were then converted from analogue to digital signals. The digitized information was then transmitted from the data processing unit to a PC via the transmission section using Bluetooth (ZEAL-S01). The wearable inertial sensor was attached to the subject's trunk (near the second lumbar vertebra) to capture the acceleration and the angular velocity signals for every physical assessment during the test. The signal from the sensor unit was recorded on a PC using a 100Hz sampling frequency.The sensor was designed in small size and lightweight. The dimension is 55 x 50 x 20[mm] while the weight is 60 gram.

2.3. Experiment

The experiment was carried out on the basis of the TUG test, which was introduced by Podsiadlo and Richardson (1991) [1]. The TUG test is a well-known screening test used by therapists worldwide to screen the balance problems and evaluate the falling risk depending on total time taken by subjects to complete the whole test. The subjects wore the wearable inertial sensors at the waist dorsally and performed the test. In choosing the location to attached the sensor to the subject, several papers have been refers. Sensor placement of wearable devices refers to the locations where the sensors are placed, and how the sensors are attached to those locations [23].

Gemperle *et al.* proposed the ergonomic guideline of *wearability* to describe the interaction between the human body and wearable objects. The *wearability map* was generalized to indicate the proper locations of a human body for unobtrusive sensor placement. These locations include the collar area, rear of upper arm, forearm, front and rear sides of ribcage, waist, thighs, shin, and top of the foot, shown in Figure 2.1. These locations have common characteristics of similar area for men and women, a relatively larger continuous surface, and low movement and flexibility [24].

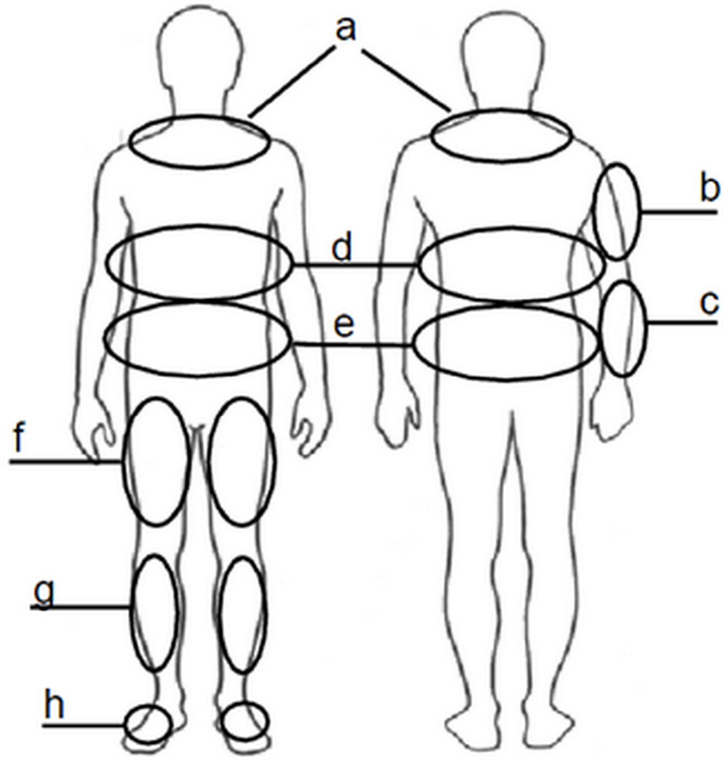


Figure 2.1: The general areas we have found to be the most unobtrusive for wearable objects are: (a) collar area, (b) rear of the upper arm, (c) forearm, (d)rear, side, and front ribcage, (e) waist and hips, (f) thigh, (g) shin, and (h) top of the foot.(Figure adapted from Gemperle, F.; Kasabach, C.; Stivoric, J.; Bauer, M.; Martin, R. Design for wearability. In Proceedings of the 2nd IEEE Symposium on Wearable Computers, Pittsburg, PA, USA, 19?20 October 1998; pp. 116-122)

Che-Chang Yang and Yeh-Liang Hsu discussed from an ergonomic point of view. They claimed that torso can better bear extra weight when carrying wearable devices. In addition, sensors or devices can be easily attached to or detached from a belt around waist level. Therefore, waist-placement causes less constraint in body movement and discomfort can be minimized as well [25]. A range of basic daily activities, including walking, postures and activity transitions can be classified according to the accelerations measured from a waist-worn accelerometer [26, 27].

Most studies adopted waist-placement for motion sensors because of the fact that the waist is close to the center of mass(COM) of a whole human body, and the torso occupies the most mass of a human body. This implies that the accelerations measured by a single sensor at this location can better represent the major human motion. Figure 2.2 illustrate the COM during standing in different position.

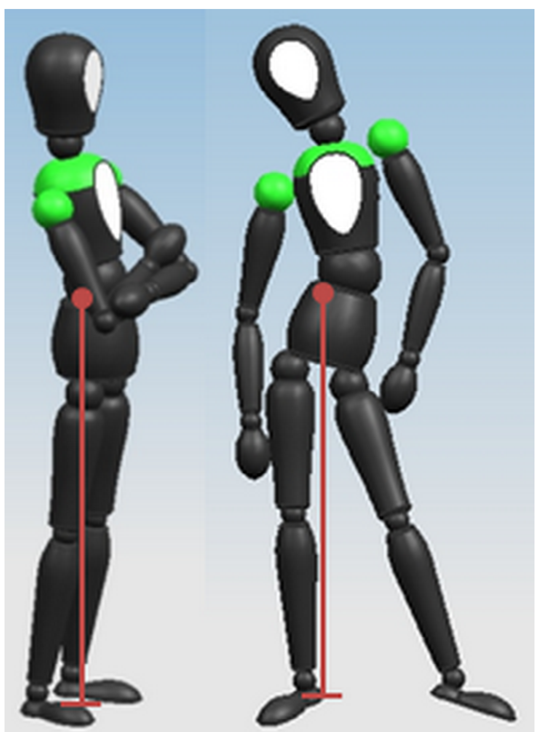


Figure 2.2: Center of mass

D.A Winter and Jian *et al.* explained the importance of centre of mass(COM) to the human balance and posture control during gait and quiet standing [28, 29]. As for example, during the release phase in initiation gait; COP will move posteriorly and towards the swing limb, thus accelerating the COM forward and towards the stance limb. Posterior COP displacement forms a deactivation of the plantar flexors and in some cases, an activation of the dorsiflexors. The lateral displacement of the COP results from a momentary loading of the swing limb (right) by the hip abductors. Unloading is achieved by a rapid activation of the stance limb hip abductors and deactivation of the right hip abductors. After unloading of the right limb the COP under the stance moves towards under the control of the plantarflexors. During this single support time the COM now accelerated forward and away from the stance limb. From illustrated trajectories during the gait initiation, we understand that the during the swing limb and stance limb also influencing the output of the sensor at the waist, which is located nearly the COM. As a result, this study decided to use only one sensor located near the COM in order to measure the parameters of falling risk. In this study, to avoid the motion artifacts, the sensor was tightly attached to the waist. Accordingly, the sensor was slotted in a belt that was attached to the waist as shown in Figure 2.7. For safety reasons, subjects did not complete the test alone;instead, a therapist was present throughout the experiment. Figure 2.3 shows the view of the TUG test, and was consulted by a therapist was as follows:

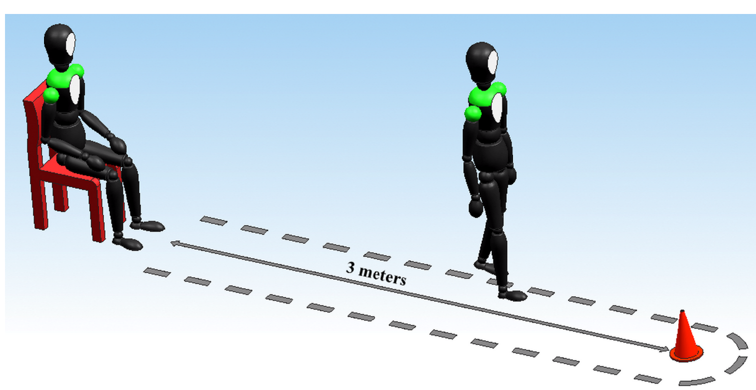


Figure 2.3: View of the TUG test set.

1. Subject sits on an armless chair with a back (approximate seat height of 46 cm).
2. Subject gets up from the chair.
3. Subject starts to walk for 3 meters away to a marked post.
4. Subject turns after reaching the marked post.
5. Subject returns to the seat, again over a distance of 3 meters.
6. Subject turns to change facing direction before sitting.

2.4. Subject

38 (male:20, female:18) elderly people average aged 65.175 $\pm$8.9 years old from Fujimoto Hayasuzu Hospital, Japan, participated in the TUG test. 27 subjects are LFR and 11 subjects are HFR. Ethical approval was obtained from Fujimoto Hayasuzu Hospital and Chiba University Ethics Committee. Previous study by Shumway-Cook *et al.* reported that the use of 13.5 seconds as a threshold achieved 87% sensitivity for multiple fallers and 87% specificity for non-fallers [5]. Accordingly, subjects were categorized as at low fall risk (LFR) upon completing the test within 13.5 seconds, while subjects who could not complete the test within that time were classified as at high fall risk (HFR).

Table 2.1: Subjects, sex and age.

Subject	Sex	Age(years)	Subject	Sex	Age(years)
Subject 1	M	59	Subject 20	F	70
Subject 2	M	78	Subject 21	M	68
Subject 3	F	78	Subject 22	M	52
Subject 4	M	67	Subject 23	F	62
Subject 5	M	71	Subject 24	M	46
Subject 6	F	78	Subject 25	M	54
Subject 7	F	73	Subject 26	F	69
Subject 8	M	71	Subject 27	M	82
Subject 9	M	66	Subject 28	F	70
Subject 10	M	71	Subject 29	M	52
Subject 11	M	70	Subject 30	F	62
Subject 12	F	56	Subject 31	F	61
Subject 13	F	57	Subject 32	M	54
Subject 14	M	64	Subject 33	F	69
Subject 15	F	68	Subject 34	M	52
Subject 16	F	70	Subject 35	F	62
Subject 17	M	62	Subject 36	F	61
Subject 18	F	69	Subject 37	F	78
Subject 19	M	77	Subject 38	M	54

2.5. Signal Analysis

It is suggested that elderly people with longer TUG test duration have a greater tendency to fall than those with a shorter time [5] as per current clinical practice. However, this approach is claimed to be insufficiently sensitive for use in a clinical context. Therefore, this study aims to show that a wearable inertial sensor could be used to provide a quantitative measure of falling risk using acceleration and angular velocity signals, applied to the TUG test. Since the TUG test consists of a sequence of basic activities, it is vital to evaluate one's ability in distinct phases or activities to make the test more sensitive.

This study proposes a single wearable inertial sensor to detect the phases in the TUG test; we also attempt to use angular velocity and angle signals to detect the phase transition. Recent studies have developed a method for detecting the phases in the TUG test. Higashi *et al.* used three wearable inertial sensors, which were attached to the trunk and thighs, to measure the angular velocity signals during the TUG test in phases [6]. The sensor attachment and unit positions by [6] displayed by Figure 2.4. In dividing the whole TUG test into phases, researcher used the acceleration signal extracted from waist sensor in roll direction, angular velocity signal in yaw and pitch direction, also from waist signal, and the angular velocity signal in pitch direction from sensor that attached to the thigh as displayed in Figure 2.5. The signal extracted from thigh was used in order to know the start of walking phase. Researcher found that when the angular velocity signal in pitch direction of the thigh exceeds the threshold; 10 deg/sec, it indicates the start of walking phase. From the Figure 2.5, it can be seen that the walking phase started when the standing phase was completed.

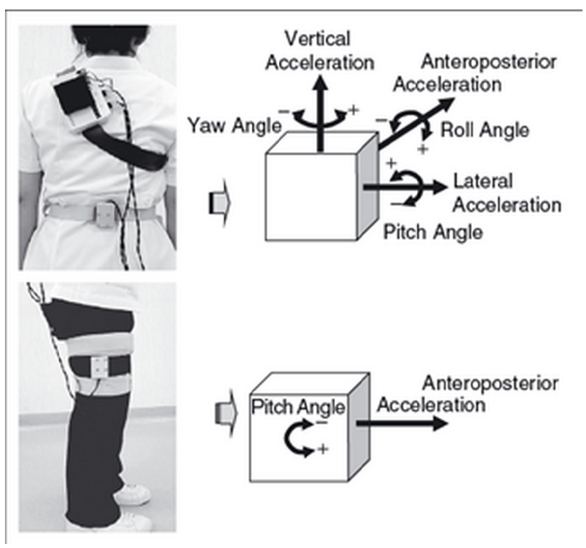


Figure 2.4: Sensor unit positions by Higashi *et al.*(Figure adapted Higashi, Y.; Yamakoshi, K.; Fujimoto, T.; Sekine, M.; Tamura, T. Quantitative evaluation of movement using the timed up-and-go test. IEEE. Eng. Med. Biol. Mag. 2008, 27, 38-46)

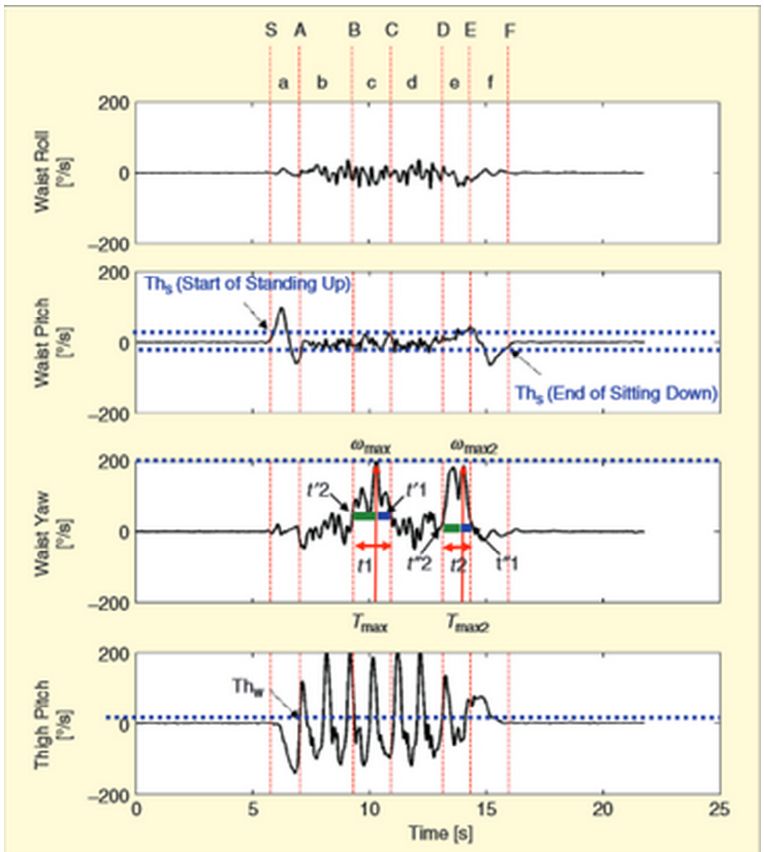


Figure 2.5: Typical angular velocities and the points at which the phase changed in a young subject during the TUG-T: (section a) standing up, (section b) walking 1, (section c) turn 1, (section d) walking 2, (section e) turn 2, and (section f) sitting down.(Figure adapted Higashi, Y.; Yamakoshi, K.; Fujimoto, T.; Sekine, M.; Tamura, T. Quantitative evaluation of movement using the timed up-and-go test. IEEE. Eng. Med. Biol. Mag. 2008, 27, 38-46)

Janura *et al.* and Schenkman *et al.* al divide the sit-stand phase into 4 phases [30, 31]. The first phase (trunk flexion) is initiated with the first recognizable movement and ends just before rising. In the second phase (momentum transfer) the body continues the forward movement and maximal dorsal flexion in the ankle joint is reached; this is the beginning of the third phase, the hip joint extension which is completed with maximal extension in the hip joint. The fourth phase (movement stabilization), in which the angular velocity equals zero, completes the entire movement. In dividing the whole TUG test into phases, we use the angular velocity and angle signals. The signal divided into 8 phases; sit-bend, bend-stand walk 1, turn 1. walk 2, turn 2, stand-bend and bend-sit. Since the Walking phase start with the ended of sit-stand phase or bend stand phase in this study, we know that the walking phase will start when the angular velocity of waist in pitch direction is = 0. As consequence, we use angle signal to detect the 0 degree, which the walking phases started. Therefore, the sensor attached at thigh is no longer required in dividing the phases replacing the 0 degree angle signal for that purpose. Figure 2.8 shows an example of a typical signal of the TUG test in normal healthy elderly subjects.

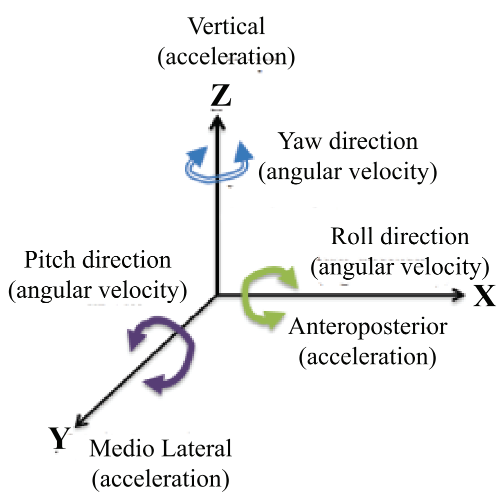


Figure 2.6: Signal directions: Antero posterior, medio lateral and vertical directions for acceleration signal, and roll, pitch and yaw directions for angular velocity signal.

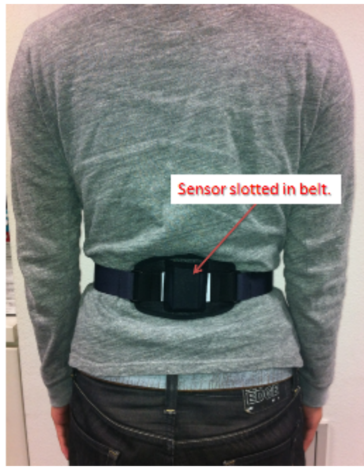


Figure 2.7: Signal direction and sensor attachment.

Initially, the TUG test was divided into six basic activities: sit-stand, walk 1, turn 1, walk 2, turn 2 and stand-sit. In this study, a more detailed approach to the phases was suggested for evaluating the differences between HFR and LFR in sit-stand phase and stand-sit phase. We divided the phases into sit-bend and bend-stand, and also stand-bend and bend-sit, becoming 8 phases in total.

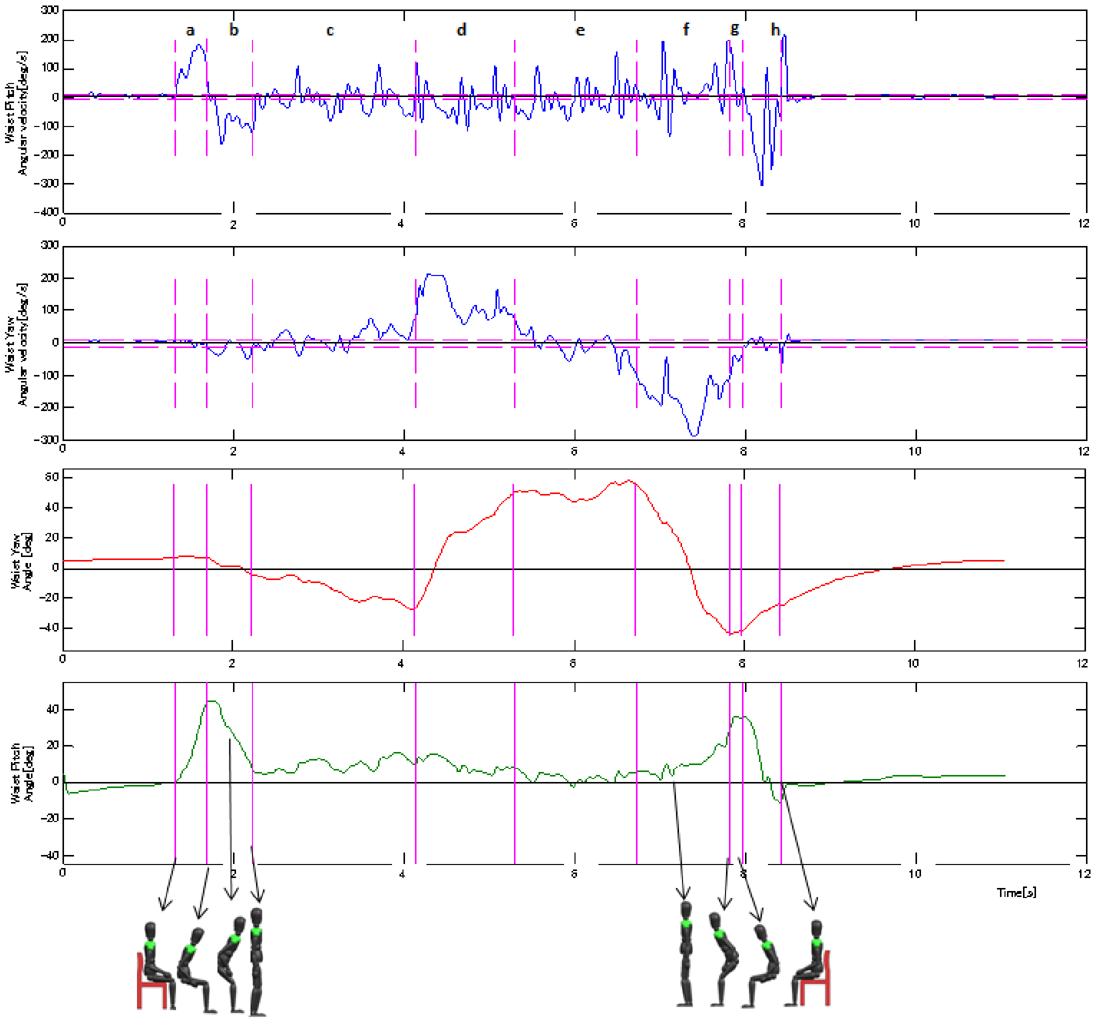


Figure 2.8: Phase point determination; a)sit-bend, b)bend-stand c)walk 1, d)turn 1, e)walk 2, f)turn 2, g)stand-bend and h)bend-sit.

1. Sit-bend

   During the sitting phase, the angle signals in the pitch direction are constant. The standing-up phase occurs as soon as the signal abruptly starts to increase. While sitting, the angle in the pitch direction is almost constant, as can be seen in Figure 2.8. From the beginning, the signals show a sudden increase. At this point, the subject starts to bend forward to stand up until a maximum angle is reached, where the subject is ready to rise up.

2. Bend-stand

   When the angle signal in the pitch direction reaches its maximum value, the maximum angle of bend is shown by the subject before he or she starts to stand up. The subject has completely stood up when the angle to an almost constant value. The stand-sit phase is also divided into two phases: stand-bend and bend-sit, for more detailed analysis.

3. Walk 1

   Stable gait starts when the subject has completely stood up. When the pitch direction of the angle signal again returns to a constant value, the walk 1 phase has started, namely, when the sit-stand phase has ended. The phase ends when the turn 1 phase starts.

4. Turn 1

   The turn 1 phase starts when the angle signal in the yaw direction starts to increase or decrease; this depends on the direction chosen by the subject, and occurs in a dramatic manner from the previous constant condition. At a certain point, the signal again becomes stable. Concurrently the turn 1 phase ends and the walk 2 phase starts.

5. Walk 2

   This phase begins with the end of the turn 1 phase. The yaw angle signal shows a constant value when the walk 2 phase starts and ends when the turn 2 phase starts.

6. Turn 2

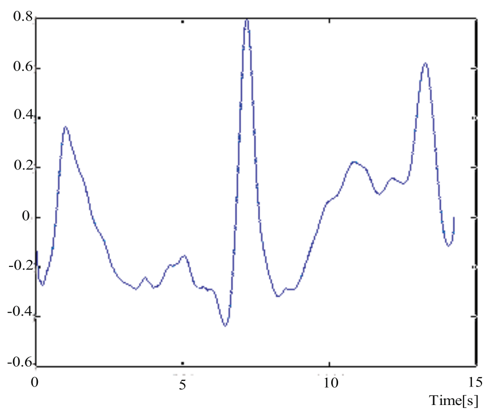
   The same method is used to determine the phase of turn 2 as in turn 1 phase. The phase begins when the angle signal in the yaw direction again starts to increase or decrease suddenly.

7. Stand-bend

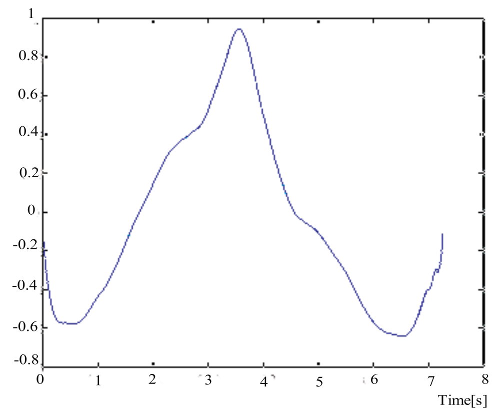
   The stand-bend phase starts after the turn 2 phase has been completed. Using the angle signal in the pitch direction, the signal increases dramatically, and when the subject is ready to sit, the maximum angle is achieved. At this time, the stand-bend phase ends.

8. Bend-sit

   The subject starts to sit when the pitch direction of angle signal decreases suddenly after its maximum level (maximum bend). The test ends when the subject completely sits as shown by the pitch direction of angle signal becoming stable again. The end point of this phase is the end point of the experiment.



(a) Cross-correlation of angle signal in pitch direction between two subjects from LFR group.



(b) Cross-correlation of angle signal in yaw direction between two subjects from LFR group.

Figure 2.9: Cross-correlation between two angle signal from subjects in LFR group.

The pattern trends of the signals between subjects are very similar. The signal's pattern measured using the wearable inertial sensor depends on the subject's movements and motions. To study the similarity between signals, each performance time was normalized, and cross correction was calculated. In order to compare the pattern similarities between the signals, the initial time delays in both signals were removed and the time delays were adjusted so that the signals were aligned in a same time range. Cross correlations were carried out in measuring the pattern signals similarity between subjects. As shown in figure 2.9, the correlation value in pitch direction between two signals is 0.8, and the correlation value between two signals in yaw direction is 0.95. These showed that the waveforms between subjects are similar in shape. However, the magnitude values measured were varied depending on the subject's motion and ability. The differences in the signals provide information between the subjects. The information is useful for determining the parameters to classify the subject is fallen into HFR or LFR.

2.5.1 TUG Derived Parameters

Various techniques have been benefited by the advent of high-performance computing in achieving practical solution to their problems. There is no exception to this in health care area. To help therapist in diagnosis and treatments, software tools have been developed to enhance the computational capabilities. This section provides the statistical method in classifying and predicting the fall risk among elderly used in this project.

In determining the fall risk among the elderly, some parameters have been identified to distinguish between HFR and LFR. The parameters were derived from the waist trunk accelerometer and angular velocity in each direction: antero posterior, medio lateral, and vertical axes, and roll, pitch, and yaw sensor axes. For additional parameters, the parameters were also derived from angle signals that were transformed from angular velocity signals. The time duration to complete the whole test and the timing characteristics for various phases were calculated in this study from acceleration signals, angular velocity signals and angular signals.

1. Total TUG test time
2. Sit-bend time
3. Bend-stand time
4. Sit-stand time
5. Walk time
6. Turn time
7. Stand-bend time

8. Bend-sit time

9. Stand-sit time

The total TUG test time is simply the time taken from angular velocity signal or angular signal. It is the time taken from the test start to its end. The angular signal was calculated from the angular velocity signal using the integration process. Apart from that, due to the gravitational effect with respect to the changes in the sensor position and orientation, the DC component acceleration signal part also counted in the calculation. The angular signal in each direction was calculated using below equations (2.1), (2.2) and (2.3):

$$Angle_{(roll)} = Angle(AC)_{gyro-roll} + Angle(DC)_{ACC-Mediolateral} \tag{2.1}$$

$$Angle_{(pitch)} = Angle(AC)_{gyro-pitch} - Angle(DC)_{ACC-Anteroposterior} \tag{2.2}$$

$$Angle_{(yaw)} = Angle(AC)_{gyro-yaw} \tag{2.3}$$

The Angular velocity signal was applied with high pass filter with cut off frequency 0.2Hz to extract AC component. Meanwhile, the acceleration signal was applied with cut off frequency 0.2Hz of low pass filter producing the DC component of the acceleration signal. Consequently, arctangent of the acceleration signal DC component was calculated to produce the DC component of angular signal, Angle (DC). Concurrently, the AC component of the angular velocity, Angle (AC) was calculated by integrating the AC component of the angular velocity, divided by the 100Hz of sampling frequency. Angular signals in each direction were calculated using different direction of the angular velocity and the acceleration signals as per listed in the above equation. The angular signal in roll direction was calculated when DC component of acceleration in the mediolateral direction added to the AC component of the angular velocity in roll direction. Meanwhile, in the case of calculating the angular velocity signal in pitch direction, the DC component of the acceleration signal in anteroposterior direction was subtracted by the integrated AC component of angular velocity signal in pitch direction. On the contrary, there is no gravitational effect in yaw direction. Therefore, in calculating the angular signal, there is no acceleration part is counted. The angular signal shows the start time when the subject bends their body before standing up and ends when the subject is completely sitting down.

To further evaluate, the RMS value was calculated. RMS value provides information on the average magnitude of accelerations and angular velocity in each direction during the test. In the acceleration signal during the walking phase shows balance during gait [36]. The RMS values were determined as shown in equation (2.4) with N are the number of X_i while X_i is the amplitude of acceleration and angular velocity signal.

$$X_{rms} = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}(X_i^2)} \tag{2.4}$$

Higher performance in gait involves a higher speed [37]. The speed parameter could also discriminate between the two groups. The equation below was used to calculate the speed in TUG gait, since the experimental involved used 3 meters of walking. Each transition phase were then analysed based on calculation using Matlab to obtain the parameters.

$$Speed = \frac{3\,meters[m]}{Walk\,time\,[s]} \tag{2.5}$$

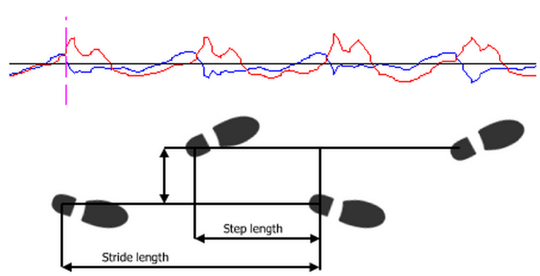


Figure 2.10: Step and stride relationship

When one heel strike; when the heel of the foot contacts the floor, to the next heel strike of the same foot is one complete gait cycle, also known as stride. Each stride is made up from two steps, each step covering the period one heel strike to heel strike of the contralateral limb. The number of step and the number of stride is measured from the acceleration signal as shown in Figure 2.10. The mean step time and the mean stride time were also calculated in this research referring to the acceleration signal, using below equations:

$$Meanstep = \frac{Walk\, time\, [s]}{\#\, gait\, step} \tag{2.6}$$

$$Meanstride = \frac{Walk\, time\, [s]}{\#\, gait\, stride} \tag{2.7}$$

Meanwhile,the rate at which strides are taken is referred to as the stride frequency or cadence. Cadence is the number of full cycles taken within a minute. Cadence correlated positively with gait and could be used to measure the performance [38].

$$Cadence = \frac{\#\, steps}{Walk\, time\, [min]} \tag{2.8}$$

The total parameters were measured from the accelerometer, angular velocity signals and angle signals were summarized in Table 2.2.

Table 2.2: Parameters in phases.

Parameters			Sit-bend	Bend-stand	Sit-stand	Walk 1	Turn 1	Walk 2	Turn 2	Stand-bend	Bend-sit	Stand-sit	Total	Sum
Time			1	1	1	1	1	1	1	1	1	1	1	11
RMS	Acceleration	AP	1	1		1		1		1	1			6
		ML	1	1		1		1		1	1			6
		V	1	1		1		1		1	1			6
	Angular Velocity	Roll	1	1		1		1		1	1			6
		Pitch	1	1		1		1		1	1			6
		Yaw	1	1		1		1		1	1			6
Amplitude	Angular Velocity	Pitch	1	1								1		3
		Yaw					1		1					2
	Angle	Pitch			1							1		2
Number of steps						1	1	1	1				1	5
Number of strides						1	1	1	1				1	5
Mean step time						1	1	1	1					4
Mean stride time						1	1	1	1					4
Cadence						1	1	1	1					4
Speed						1		1						2
													Total	78

Note:AP=Anteroposterior, ML=Mediolateral, V=Vertical.

2.5.2 T-Test

In reporting the hypothesis with the conclusion, author used the p-value. A p-value is the probability of observation data that a less compatible with the null hypothesis by chance than data that are observed if the null hypothesis were true. Figure 2.11 illustrates the distribution curve for a test statistic under a null hypothesis with two possible alternative hypothesis.

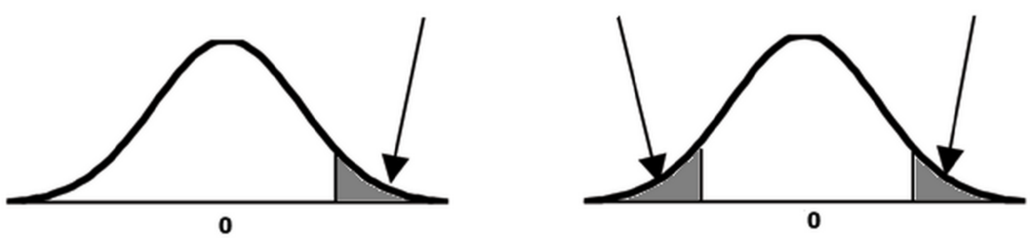


Figure 2.11: Probability p-value

The p-value is the area under the null hypothesis distribution curve starting at the observed test statistic value extending in the direction of the alternative hypothesis. If the alternative is one sided, the p-value is the area under the curve in one tail of the distribution. If the alternative is two-sided, the p-value is the area under the curve in both tails of the distribution.The p-value can be used to decide wether or not to reject a given null hypothesis after viewing the data. If the p-value is small, we could conclude that the observed data are unlikely to have generated by a mechanism that conforms with the null hypothesis; and thus we reject the null hypothesis in favour of the alternative hypothesis. If the p-value is large, we do not have enough evidence against the null hypothesis; we fail to reject the null hypothesis. The p-value is compared against the significant level α as we used α =0.05. A p-value is small is $p< \alpha$, while it is considered large if $p\geq \alpha$.

t-test are among of the most frequently used testing procedure in biological sciences. t-test are designed for three distinct application;(1)for comparing the mean of one single population to a fixed constant(one-sample t-test), (2) for comparing the means of two independent populations to each other(Two-sample t-test), and finally(3) for comparing two dependent measurement(paired t-test). A two-tailed student t-test was used in this study to test whether the differences between the LFR and HFR were statistically significant.

2.5.3 K Nearest Neighbor

For classification purposes, K nearest neighbors (KNN), also known as the lazy learning algorithm, that is a very intuitive method that classifies unlabelled examples on the basis of their similarities to an example in a training set. It is a simple algorithm that works using minimum distance from the query instance to the training samples to determine the KNN [39]. After the k nearest neighbors are obtained, the simple majority of these K nearest neighbors are taken to predict the query instance. This was carried out to predict whether the subject is belongs to HFR or LFR group in this study. The data for KNN algorithm consist of several multivariate attributes: namely x_i is the test subject, used to classify Ydata subject. In this study, 2 of 11 subjects from HFR and 7 of 27 subjects from LFR were used as test subjects. The Euclidean distance function was used with k=5 (using the 5 nearest neighbors) as the class number of this algorithm. The distance between the query instance and all the training samples was then calculated. Euclidean distance (d_E) was measured using equation (4):

$$d_E(x, y) = \sqrt{\sum_{i=0}^{k-1}(x_i - y_i)^2} \tag{2.9}$$

In order to classify the fall risk among elderly, previous study classified the were using 1-dimensional of time parameter. In this study, 78 parameters were obtained from extracted acceleration signal, angular velocity signal and transformed angular signal. From extracted 78 parameters, 44 parameters were identified significant differences between the two groups. The multivariate analysis could facilitated the classification between LFR and HFR using all 44 significant parameters.

2.5.4 Principle Component Analysis

k-NN analysis method are computationally simple but lack of ability to classify the subject using multiple parameters. To further improve the classification using multivariate data analysis technique have been used in this study. Principle Component Analysis (PCA) designed to extract and display a systematic variation in data matrix. Due to difficulty in visualizing a multi-dimensional space, PCA hs being used to reduce the dimensionality of multi-attributes to two or three dimensions. PCA summarizes the variation in a correlated multi-attributes to a set of uncorrelated components; which is a particular linear combination of the original variables. The extracted uncorrelated components are called principal component(PC) and are estimated from the eigenvectors of the covariance or correlation matrix of the original variables. The objective of PCA is to achieve parsimony and reduce dimensionality by extracting the smallest number components that account for most of the variation in the original multivariate data and to summarize the data with little loss of information. Statistically PCA find lines, planes and hyperplanes in the K-dimensional space that approximate the data as well as possible in the least square sense. As shown in Figure 2.12, the line or a plane that is the least square approximation of a set of data points make the variance of the coordinates on the line or plane as large as possible.

In order to transform the data to a form suitable for analysis, the data need to be scaled or normalized. The mean-centering normalization had being used in this study. After the mean-centering and scaling to unit variance, the data set is ready for the first principal component(PC1) computation. This component is the line in the K-dimensional space that best approximates the data in the least square sense. This line goes through the average point; such that the average point is the origin after the normalization process. Each observation may now be projected onto this line in order to get a coordinate value along the PC line. This new coordinate value is known as a *score*.

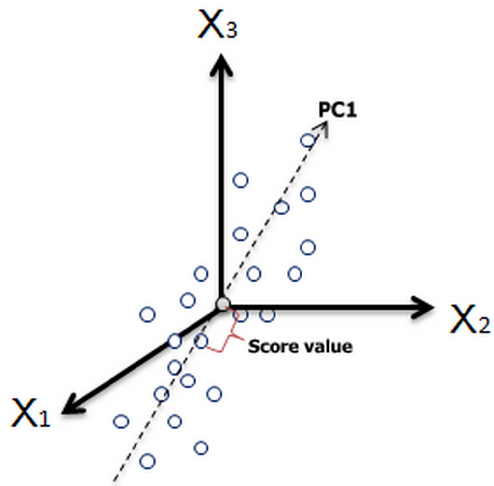


Figure 2.12: The first principal component,PC1 and the score value.

Usually only one principal component is insufficient enough to model a systematic variation of a data set. Thus, a second principal component, PC2 is considered. The second PC is also represented by a line in the K-dimensional variable space; which is orthogonal to the first PC as shown in Figure 2.13.

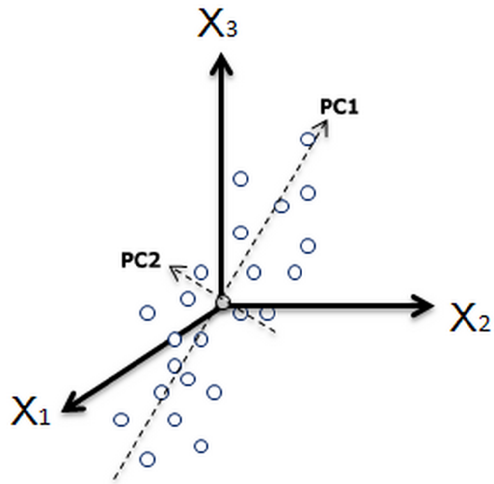


Figure 2.13: The second principal component,PC2 being orthogonal to PC1.

Two principal component will define a plane when they derived together, with k-dimensional variable space as illustrate in Figure 2.14. By projecting all the observations onto this low-dimensional sub-space and plotting the results, it is possible to visualize the structure of the data set. The coordinates values of the observation on this plane is called *scores*, and hence the plotting such a projected configuration is known as a score plot.

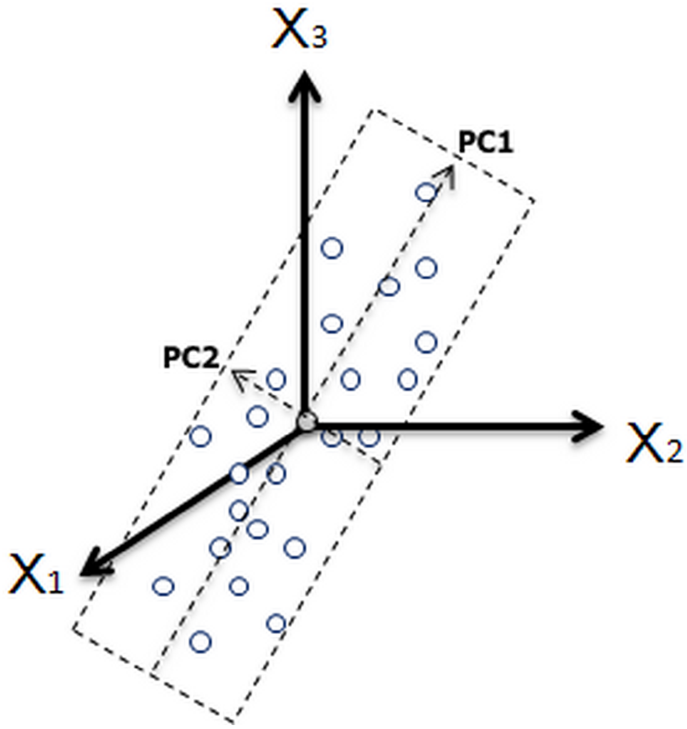


Figure 2.14: Two PCs form a plane.

In a PCA model with a plane in K-space, we concern which variables are accounted for the pattern among the observation. Variables that influences the pattern and the correlation between the variables are required to be determine.Such knowledge is given by the principal component *loadings*. PC *loadings* are correlation coefficient between the PC scores and the original variables. It measure the importance of each variable in accounting for the variability in the PC. It is possible to interpret the first few PCs in terms of 'overall' effect or a 'contrast' between groups of variables based on the structures of PC loadings. high correlation between PC1 and a variable indicates that the variable is associated with the direction of the maximum amount of variation in the dataset. More than one variable might have a high correlation with PC1. A strong correlation between a variable and PC2 indicates that the variable is responsible for the next largest variation in the data perpendicular to PC1, and so on. If a variable does not correlate to any PC, or correlates only with the last PC, or one before the last PC, this usually suggests that the variable has little or no contribution to the variation in the dataset. Therefore, PCA may often indicate which variables in a dataset are important and which ones may be of little consequence. Some of these low-performance variables might therefore be removed from consideration in order to simplify the overall analyses. In this study, applying the PCA to the 44 significant parameters for 38 observation would be compressed or reduce to fewer principal components that can be displayed graphically with minimal loss of information. The previous study using only a parameter at once in classifying the elderly with fall risk would be improve using several parameters that are believe to be important to the test.

2.5.5 Linear Discriminant Analysis

There are many possible techniques for classification of data. Principal Component Analysis (PCA and Linear Discriminant Analysis (LDA) are two commonly used techniques for data classification and dimensionality reduction. Linear Discriminant Analysis easily handles the case where the within-class frequencies are unequal and their performances has been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. We decided to implement an algorithm for LDA in hopes of providing better classification compared to Principal Components Analysis. The prime difference between LDA and PCA is that PCA does more of feature classification and LDA does data classification. In PCA, the shape and location of the original data sets changes when transformed to a different space whereas LDA does not change the location but only tries to provide more class separability and draw a decision region between the given classes. This method also helps to better understand the distribution of the feature data.

Discriminant Function Analysis (DA) undertakes the same task as multiple linear regression by predicting an outcome. However, multiple linear regression is limited to cases where the dependent variable on the Y axis is an interval variable so that the combination of predictors will, through the regression equation, produce estimated mean population numerical Y values for given values of weighted combinations of X values. DA is used when the dependent is categorical with the predictor IVfs at interval level such as age, income, attitudes, perceptions, and years of education, although dummy variables can be used as predictors as in multiple regression. Logistic regression IVfs can be of any level of measurement. It is also used when there are more than two DV categories, unlike logistic regression, which is limited to a dichotomous dependent variable.

Discriminant analysis linear equation DA involves the determination of a linear equation like regression that will predict which group the case belongs to. The form of the equation or function is:

$$D = v_1 X_1 + v_2 X_2 + ... v_i X_i + a \tag{2.10}$$

Where D = discriminate function v = the discriminant coefficient or weight for that variable X = respondent's score for that variable a = a constant i = the number of predictor variables

After using an existing set of data to calculate the discriminant function and classify cases, any new cases can then be classified. The number of discriminant functions is one less the number of groups. There is only one function for the basic two group discriminant analysis.

There are several purposes of DA:

1. To investigate differences between groups on the basis of the attributes of the cases, indicating which attributes contribute most to group separation. The descriptive technique successively identifies the linear combination of attributes known as canonical discriminant functions (equations) which contribute maximally to group separation.

2. Predictive DA addresses the question of how to assign new cases to groups. The DA function uses a person's scores on the predictor variables to predict

the category to which the individual belongs.

3. To determine the most parsimonious way to distinguish between groups.

4. To classify cases into groups.

5. To test theory whether cases are classified as predicted.

The aim of the statistical analysis in DA is to combine (weight) the variable scores in some way so that a single new composite variable, the discriminant score, is produced.

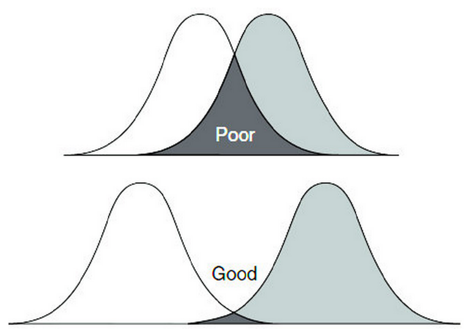


Figure 2.15: Discriminant Distribution.

The top two distributions in Figure 2.15 overlap too much and do not discriminate too well compared to the bottom set. Misclassification will be minimal in the lower pair, whereas many will be misclassified in the top pair. Standardizing the variables ensures that scale differences between the variables are eliminated. When all variables are standardized, absolute weights can be used to rank variables in terms of their discriminating power, the largest weight being associated with the most powerful discriminating variable. Variables with large weights are those which contribute mostly to differentiating the groups. As with most other multivariate methods, it is possible to present a pictorial explanation of the technique. The following example uses a very simple data set, two groups and two variables. If scatter graphs are plotted for scores against the two variables, distributions like those in Figure 2.16 are obtained.

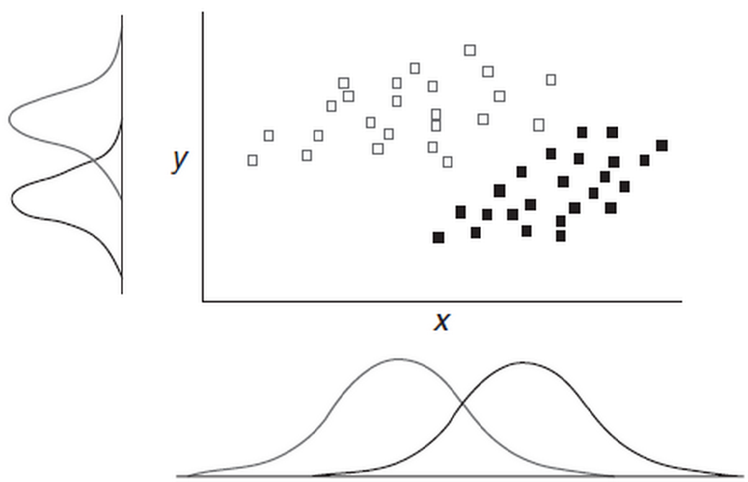


Figure 2.16: Scattergraph displaying distributions by axis.

The new axis represents a new variable which is a linear combination of x and y, it is a discriminant function as shown in Figure 2.17. Obviously, with more than two groups or variables this graphical method becomes impossible. Clearly, the two groups can be separated by these two variables, but there is a large amount of overlap on each single axis (although the y variable is the 'better' discriminator). It is possible to construct a new axis which passes through the two group centroids ('means'), such that the groups do not overlap on the new axis. In a two-group situation predicted membership is calculated by first producing a score for D for each case using the discriminate function. Then cases with D values smaller than the cut-off value are classified as belonging to one group while those with values larger are classified into the other group. D scores is called new variables. The group centroid is the mean value of the discriminant score for a given category of the dependent variable. There are as many centroids as there are groups or categories. The cut-off is the mean of the two centroids. If the discriminant score of the function is less than or equal to the cut-off the case is classed as 0, whereas if it is above, it is classed as 1.

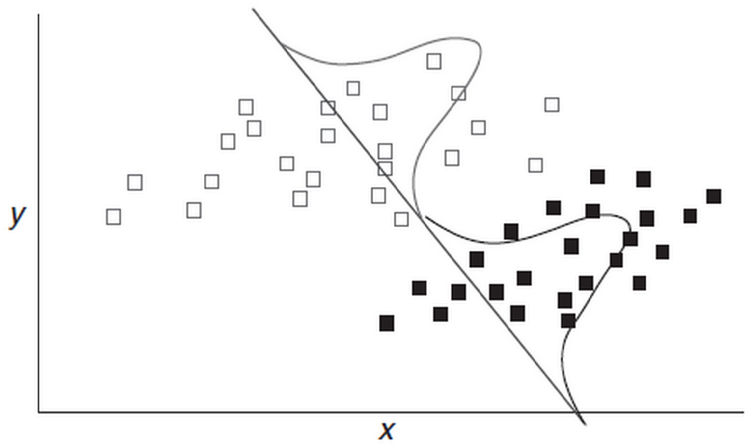


Figure 2.17: New axis creating greater discrimination.

2.5.6 Random Forest

Decision tree or sometimes called as classification trees are one of the most widely used machine learning methods for modelling the relationship between one of more attributes and a discrete endpoint [40]. A decision tree classifies subjects by sorting them through a tree from node to node where each node is an attribute with a decision rule that guides that subject through different branches of tree to a leaf that provides its classification. the primary advantage of this approach is that it is simple and the resulting tree can be interpreted as IF-THEN rules that are easy to understand. Random Forest(RF) build on the decision tree idea and have been used to detect and the gene-environment interaction in genetic studies. A RF is a collection of individual decision tree classifiers, where each tree in the forest has been trained using a bootstrap sample of from the data, and each attribute in the tree is chosen from among a random subset of attributes [41].

In this study, individual tree are constructed by selecting n samples from 38 subjects with 78 attributes or parameters. Following are the steps in tree growth in random forest:

1. Training set(n) were chose by selecting from n sample subjects, with replacement(ntree=200) from the data.

2. At each node in the tree, m attributes from the entire set of 78 parameters in the data were randomly selected with the magnitude of m is constant throughout the forest building. About one-third of the attribute used as the training.

3. At each node, the best split chosen from among the m attributes and until the tree is fully grown(no pruning).

4. Repetition of this algorithm yields a forest of trees, each of which have been trained on bootstrap samples of instances. Thus for 2000 ntree, certain instances will have been left out during training. Prediction error was estimated from these out-of-bag(OOB) instances. The OOB instances are also used to estimate the importance of particular attributes via permutation testing. Finally, the average effect is calculated across all trees to yield the variable importance value. If randomly permuting values of a particular attribute does not affect the predictive ability of trees on OOB samples, that attributes is assigned a low importance score.

Chapter 3

Results

Rasulullah saw said: "None of you should long for death, for if he is a good man, he may increase his good deeds, and if he is an evil-doer, he may stop the evil deeds and repent."

Bukhari

3.1. Introduction

Falls are a major problem to elderly health and independence. There are many factors contribute to the fall risk among elderly. Subjective method such as diaries, questionnaires and survey are inexpensive tools leads to inconsistent result considering they depends on the individual observation and interpretation.

Assuming that physical factors are significant contributors to the fall risk problem, several standard physical test has been developed by researcher in order to determine the fall risk among elderly. Standard test of physical activity assessment such as timed up and go test (TUG test), four square step test(FSST), 10 meter walking and others also require subjective judgement that measures the time taken to complete the assessment by stopwatch. To improve, a new method using 3-D motion capture system(VICON) has been developed. The system provide an accurate results. However, the system is very costly and have limited space to operate and immobile.

By using an objective techniques, wearable inertial sensor, enable quantitative evaluation device in a simple, compact ,mobile and could prevent the inaccurate result due to subjective individual observation. Furthermore, the quantitative provided by the signals extracted from the sensor reveal the movement activities of the subject well beyond simply the time taken from the TUG test.

3.2. Quantitative Analysis

Table 3.1: Mean and standard deviation of each derived parameter for HFR and LFR.

Bil	Parameter * p<0.05	Low fall risk Mean ± std	High Fall risk Mean ± std
P1	sit-bend time[s]	0.7 ± 0.21	0.68 ± 0.27
P2	bend-stand time[s] (p=0.08)	0.74 ± 0.28	1.03 ±0.50
P3	sit-stand time[s]	1.44 ± 0.36	1.72 ±0.74
P4	walk 1 time[s] *	2.21 ± 0.67	4.07 ± 1.07
P5	turn 1 time[s] *	1.61 ± 0.48	2.50 ±0.69
P6	walk 2(return) time[s] *	2.41 ± 0.67	3.87 ±0.66
P7	turn 2 time[s] *	1.18 ±0.37	1.77 ±0.40
P8	stand-bend time[s] *	1.09 ±0.35	1.66 ±0.46
P9	bend-sit time[s] *	0.87 ± 0.24	1.28 ±0.30
P10	stand-sit time[s] *	1.95 ± 0.50	2.94 ±0.73
P11	TUG total measured time[s] *	10.09 ± 1.86	15.77 ±1.41
P12	Amplitude angular velocity pitch, sit-bend[deg/s]	122.88 ± 52.84	119.98 ± 43.70
P13	Amplitude angular velocity pitch,bend-stand[deg/s]	89.45 ± 43.62	77.54 ± 33.69
P14	Amplitude angular velocity pitch, stand-sit[deg/s]	144.97 ± 70.44	104.07 ± 56.74
P15	Amplitude angular velocity Yaw, Turn 1[deg/s] *	165.88 ± 38.31	107.09 ± 27.11
P16	Amplitude angular velocity Yaw, Turn 2[deg/s] *	200.14 ± 48.04	123.38 ± 35.46
P17	Amplitude angle roll, sit-stand[deg]	28.35 ± 11.64	30.58 ± 14.02
			Continued on next page

Table 3.1 – continued from previous page

Bil	Parameter * p<0.05	Low fall risk Mean ± std	High Fall risk Mean ± std
P18	Amplitude angle pitch, stand-sit[deg]	33.83 ± 11.06	36.64 ± 11.67
P19	RMS acceleration AP sit-bend	0.32 ± 0.11	0.38 ± 0.12
P20	RMS acceleration AP bend-stand	0.29 ± 0.11	0.31 ± 0.14
P21	RMS acceleration AP stand-bend	0.34 ± 0.11	0.35 ± 0.09
P22	RMS acceleration AP bend-sit	0.39 ± 0.12	0.44 ± 0.14
P23	RMS acceleration ML sit-bend	0.07 ± 0.03	0.06 ± 0.03
P24	RMS acceleration ML bend-stand	0.11 ± 0.03	0.10 ± 0.04
P25	RMS acceleration ML stand-bend	0.19 ± 0.07	0.16 ± 0.05
P26	RMS acceleration ML bend-sit	0.09 ± 0.05	0.09 ± 0.04
P27	RMS acceleration V sit-bend	0.14 ± 0.07	0.15 ± 0.07
P28	RMS acceleration V bend-stand *	0.21 ± 0.10	0.16 ± 0.05
P29	RMS acceleration V stand-bend *	0.19 ± 0.06	0.13 ± 0.04
P30	RMS acceleration V bend-sit	0.21 ± 0.12	0.16 ± 0.08
P31	RMS angular velocity roll sit-bend	9.41 ± 5.39	7.12 ± 4.09
P32	RMS angular velocity roll bend-stand	13.87 ± 4.39	11.52 ± 4.38
P33	RMS angular velocity roll stand-bend *	26.59 ± 11.92	17.14 ± 5.42
P34	RMS angular velocity roll bend-sit *	12.22 ± 6.77	8.66 ± 2.76
P35	RMS angular velocity pitch sit-bend	68.49 ± 33.19	76.28 ± 45.16
P36	RMS angular velocity pitch bend-stand	53.86 ± 21.11	44.88 ± 16.82
P37	RMS angular velocity pitch stand-bend *	46.97 ± 17.49	29.66 ± 11.33
P38	RMS angular velocity pitch bend-sit *	75.70 ± 38.28	48.29 ± 17.57
P39	RMS angular velocity yaw sit-bend	12.68 ± 8.76	10.94 ± 7.14
P40	RMS angular velocity yaw bend-stand	21.90 ± 9.86	22.58 ± 8.32
P41	RMS angular velocity yaw stand-bend *	97.08 ± 37.78	55.28 ± 17.37
P42	RMS angular velocity yaw bend-sit	23.75 ± 10.49	20.45 ± 6.83
P43	RMS acceleration AP walk 1 *	0.22 ± 0.08	0.13 ± 0.049
P44	RMS acceleration AP walk 2(return) *	0.20 ± 0.056	0.14 ± 0.055
P45	RMS acceleration ML walk 1 *	0.22 ± 0.080	0.14 ± 0.055
P46	RMS acceleration ML walk 2(return) *	0.20 ± 0.057	0.14 ± 0.044

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Table 3.1 – continued from previous page

Bil	Parameter * p<0.05	Low fall risk Mean ± std	High Fall risk Mean ± std
P47	RMS acceleration V walk 1 *	0.28 ± 0.091	0.15 ± 0.055
P48	RMS acceleration V walk 2(return) *	0.26 ± 0.08	0.15 ± 0.038
P49	RMS angular velocity Roll walk 1 *	20.59 ± 7.3	11.99 ± 5.261
P50	RMS angular velocity Roll walk 2(return) *	20.11 ± 5.037	12.35 ± 4.659
P51	RMS angular velocity Pitch walk 1 *	47.54 ± 21.501	19.24 ± 8.901
P52	RMS angular velocity Pitch walk 2(return) *	41.40 ± 15.755	20.10 ± 7.176
P53	RMS angular velocity Yaw walk 1 *	34.47 ± 9.343	24.96 ± 11.521
P54	RMS angular velocity Yaw walk 2(return) *	35.22 ± 11.793	25.89 ± 8.283
P55	Number of walk 1 steps *	6 ± 1.37	7 ± 1.10
P56	Number of walk 2 steps *	5 ± 1.58	7 ± 1.29
P57	Number of turn 1 steps (p=0.09)	3 ± 0.92	4 ± 1.62
P58	Number of turn 2 steps *	2 ± 0.72	3 ± 1.05
P59	Number of Total steps *	16 ± 2.74	21 ± 2.05
P60	Number of walk 1 strides *	3 ± 0.68	4 ± 0.55
P61	Number of walk 2 strides *	3 ± 0.79	4 ± 0.64
P62	Number of turn 1 strides (p=0.09)	1 ± 0.46	2 ± 0.81
P63	Number of turn 2 strides*	1 ± 0.29	1 ± 0.53
P64	Number of total strides *	8 ± 1.37	11 ± 1.02
P65	Mean step time walk 1[s] *	0.42 ± 0.15	0.56 ± 0.13
P66	Mean step time turn 1[s]	0.66 ± 0.42	0.91 ± 0.88
P67	Mean step time walk 2[s] (p=0.057)	0.47 ± 0.14	0.56 ± 0.12
P68	Mean step time turn 2[s]	0.78 ± 0.39	0.73 ± 0.35
P69	Mean stride time walk 1[s] *	0.83 ± 0.31	1.12 ± 0.27
P70	Mean stride time turn 1[s]	1.32 ± 0.84	1.82 ± 1.76
P71	Mean stride time walk 2[s] (p=0.057)	0.93 ± 0.28	1.11 ± 0.24
P72	Mean stride time turn 2[s]	1.56 ± 0.79	1.47 ± 0.70
P73	cadence walk 1[step/min] *	144.55 ± 33.83	112.42 ± 25.81
P74	cadence walk 2[step/min] *	129.7 ± 30.82	112.96 ± 25.37
P75	cadence turn 1[step/min] *	154.83 ± 49.13	99.4 ± 52.60

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Table 3.1 – continued from previous page

Bil	Parameter * p<0.05	Low fall risk Mean ± std	High Fall risk Mean ± std
P76	cadence turn 2[step/min]	78.44 ± 36.49	95.02 ± 32.48
P77	Speed walk 1 [m/s] *	1.27 ± 0.28	0.79 ± 0.22
P78	Speed walk 2 [m/s] *	1.26 ± 0.30	0.80 ± 0.14

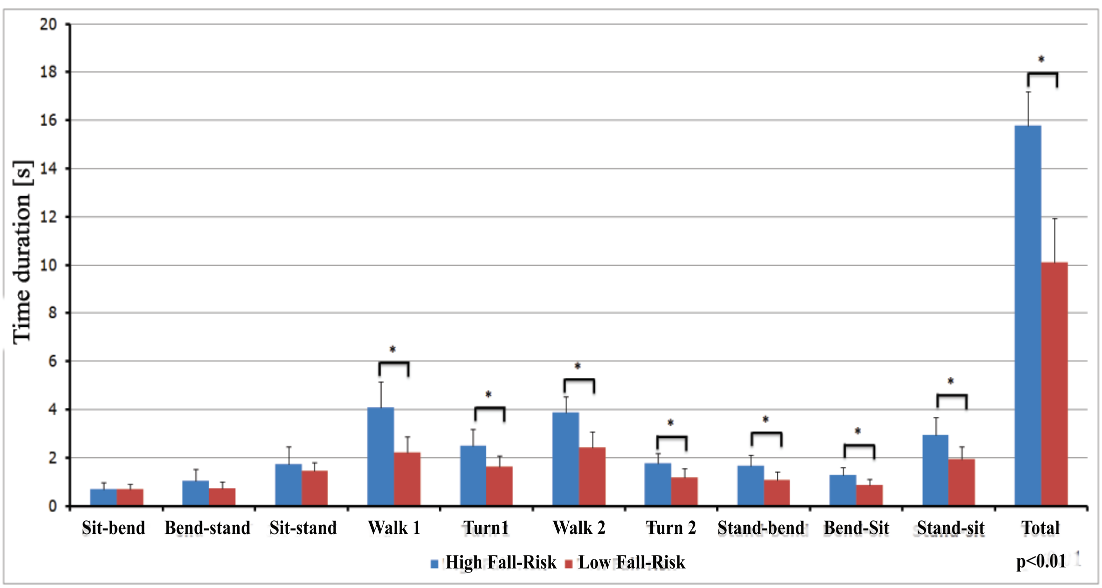
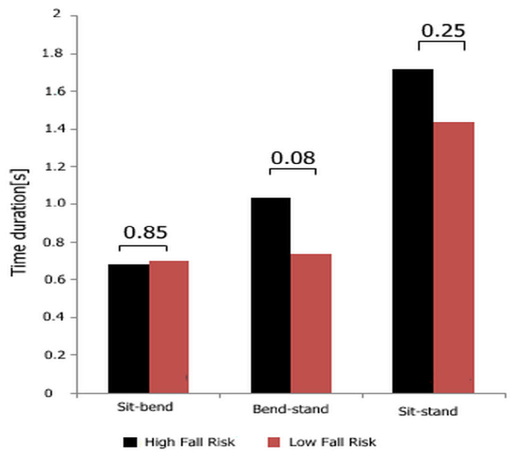
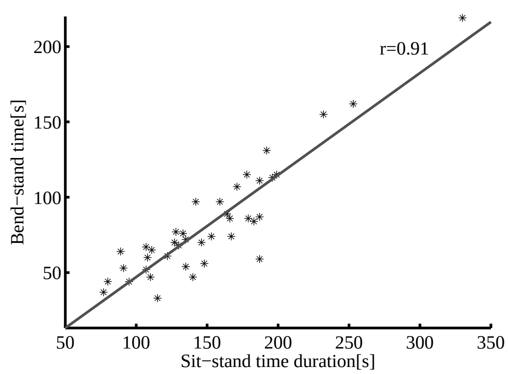


Figure 3.1: A comparison between HFR and LFR groups in total duration parameter and in each phase.

The result shown in Figure 3.1 indicate that the subjects in the HFR group took longer to complete the whole test For each phase, there were significant differences in all activity phases, except for the sit-stand phase, which comprised of sit-bend and bend-stand phases.



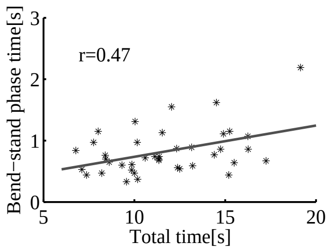
(a) A comparison between HFR and LFR in terms of time parameters for sit-bend, bend-stand, and sit-stand phases.



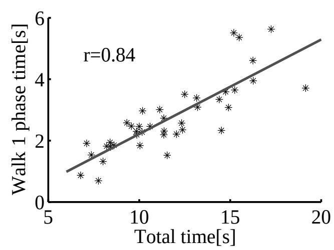
(b) Correlation between duration of sit-stand phase and duration of bend-stand phase.

Figure 3.2: Dividing the Sit-stand phase into more details phases.

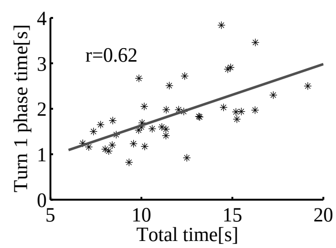
It can be seen in Figure 3.2 that, lower p-value (p=0.08) was noted in bend-stand phase and greater (p=0.85) in sit-bend phase compared to sit-stand (p=0.25). This suggests that the sit-bend phase contributed to the high p-value in sit-stand phase. Consequently, bend-stand phase was chosen to represent the activity difference between HFR and LFR in sit-stand phase. In order to validate this approach, correlations of the durations taken for the bend-stand phase and the sit-stand phase were determined for both HFR and LFR groups. High correlation results between the two phases were determined for all subjects, as shown in Figure 3.2(b), with r=0.91.Although the p-values were very low in the bend-stand phase, the result could not be used in differentiating the two groups, when considering that α <0.05 was used in this study.



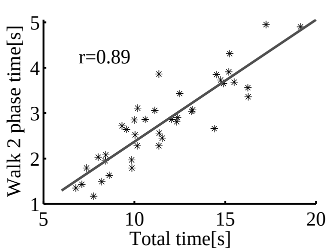
(a) Bend-stand phase



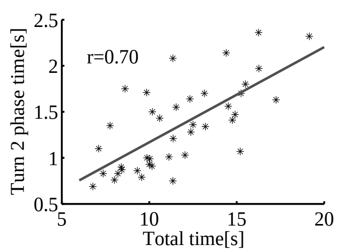
(b) Walk 1 phase



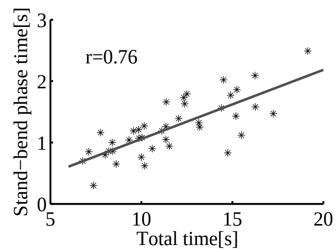
(c) Turn 1 phase



(d) Walk 2 phase



(e) Turn 2 phase



(f) Stand-bend phase

Figure 3.3: Correlation between time duration in each phase with total time.

To investigate the relationship between the activity in each phase and TUG test duration, the correlation between time taken in each phase and total time taken to complete the whole test was plotted. Strong correlations were identified, as shown in Figure 3.3(b) and Figure 3.3(d), for walking phases. Strong correlation also found in turning, stand-bend, and stand-sit phases. Despite this, low r values were found as shown in Figure 3.3(a) for bend-stand. It may be reasonable to suppose that the low correlations in the sit-stand and the bend-stand phases were caused by the static movement during these phases, rather than the dynamic activities of walking and turning. Since the time parameter could not identify any significant differences in this phase, RMS parameter was considered.

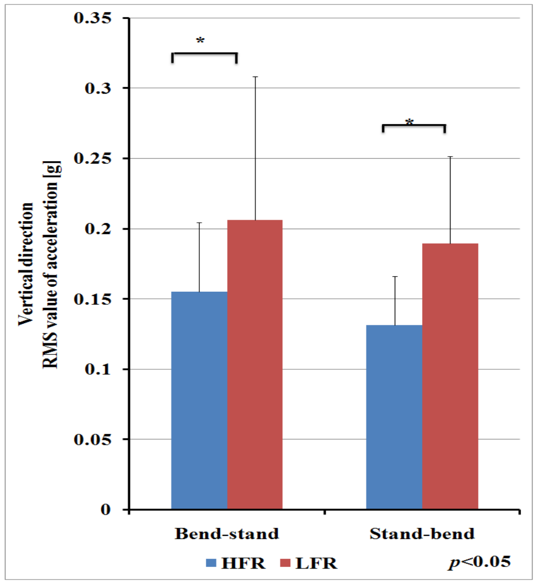


Figure 3.4: Comparison between HFR and LFR in RMS parameter for bend-stand and stand-bend phases in vertical direction of acceleration signal.

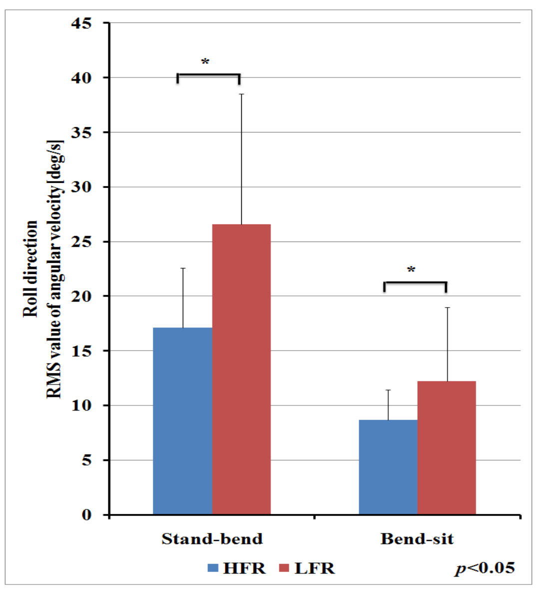


Figure 3.5: Comparison between HFR and LFR in RMS parameter for stand-bend and bend-sit phases in roll direction of angular velocity signal.

A significant difference was found in the RMS value of the acceleration signal in a vertical direction, with $p<0.05$ in bend-stand phase and in stand-bend phase, as shown in Figure 3.4. Data suggested that LFR subjects move with higher acceleration. Significant differences were displayed in the acceleration signal in the roll direction for stand-bend and bend-sit phases, with subjects in the HFR group having higher RMS values.

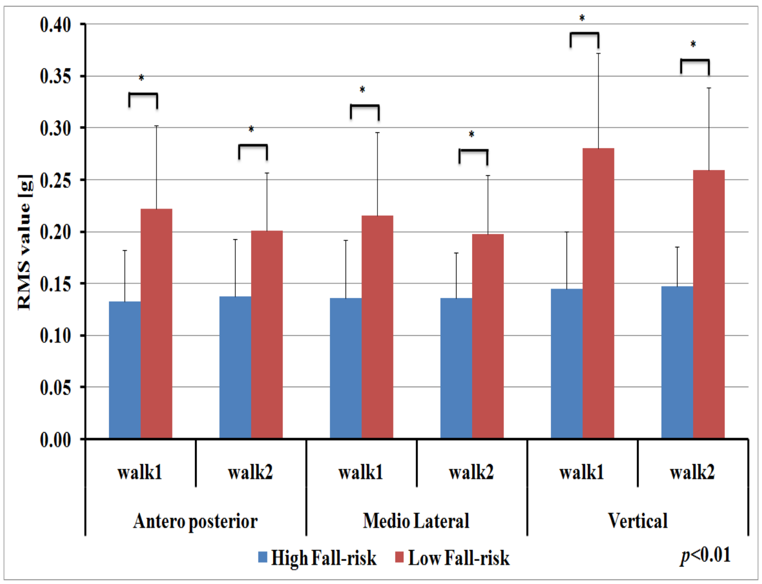


Figure 3.6: A Comparison between HFR and LFR in RMS parameter for walk 1 and walk 2 phases using acceleration in all directions.

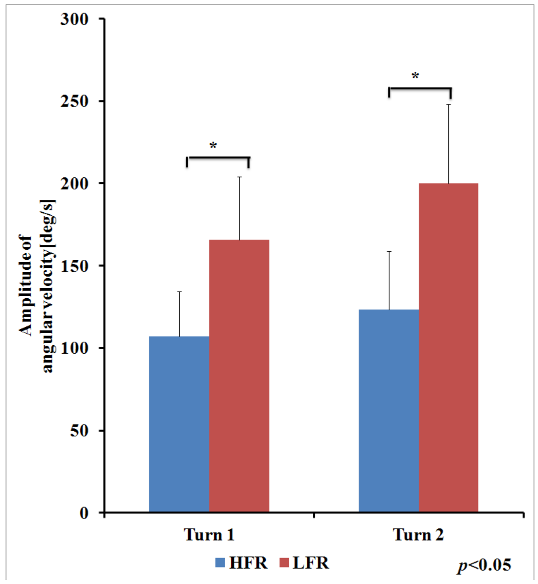


Figure 3.7: A Comparison between HFR and LFR in amplitude parameter using angular velocity signal in yaw direction for turn 1 and turn 2 phases

In other phases, besides the time parameter, other parameters were also used and showed significant differences. For the walking phase, acceleration signal and angular velocity signal in all directions showed significant differences with $p<0.01$, as shown in Figure 3.6. Significant differences were found in the yaw direction of angular velocity signal, referring to the amplitude parameter, with $p<0.01$. Using the cadence parameter, significant differences were observed only in walk 1, walk 2, and turn 1 phases, with $p<0.01$. During the turn 2 phase, only 1 to 3 steps were required to complete the phase, leading to the insignificant difference between the two groups. Comparing the speed parameters, the HFR group had lower walking speed with $p<0.01$ for both walk 1 and walk 2 phases. For each parameter, numerical results were derived and are summarised in Table 3.1.

3.3. Classification Analysis

In previous section, 78 parameters were obtained from extracted acceleration signal, angular velocity signal and transformed angular signal. There are 44 parameters were identified significant differences between the two groups. Classification using more parameters could provides more sensitive data. In order to classify the subject into HFR and LFR using all the significant parameters, we tried to use from the simplest classification algorithm; K-nn, to the multivariate analysis methods; principal component analysis (PCA) and linear discriminant analysis(LDA), and also random forest analysis.

3.3.1 K Nearest Neighbor

From the various parameters, classification between the two groups was obtained. Current practice involves using the total test duration to predict subjects to be classified into HFR or LFR groups. Here, classification using two parameters based on k-NN was carried out.

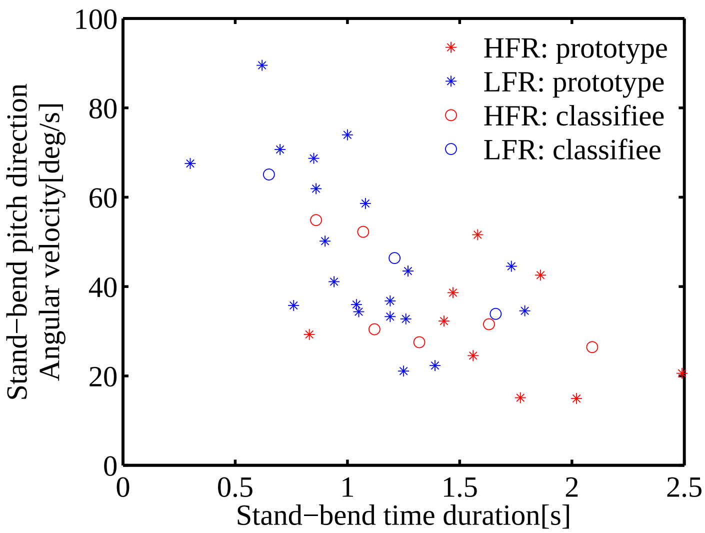


Figure 3.8: Classification between HFR and LFR groups using k-NN classifier for stand-bend phase.

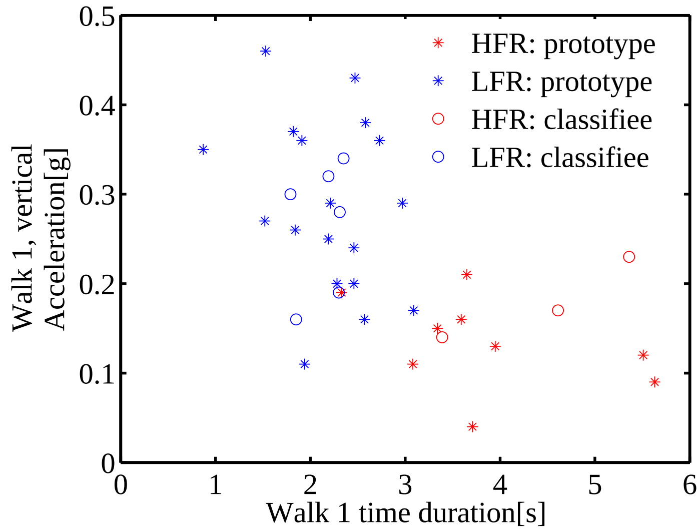


Figure 3.9: Classification between HFR and LFR groups using k-NN classifier for walking phase.

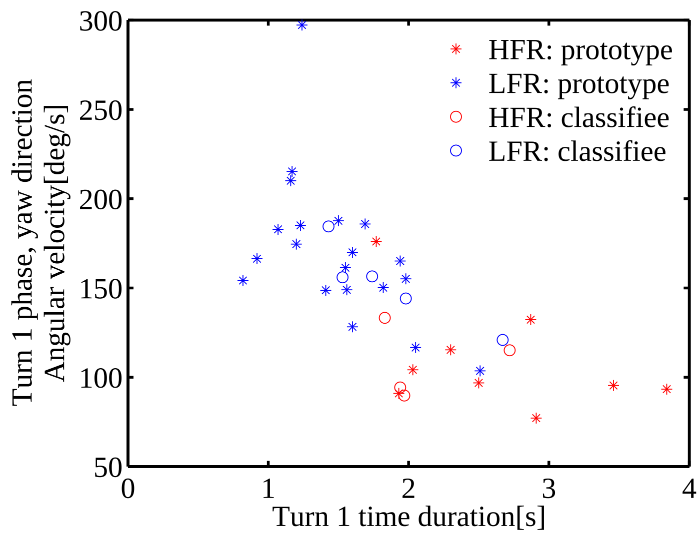


Figure 3.10: Classification between HFR and LFR groups using k-NN classifier for turning phase.

Figure 3.8,Figure 3.9,Figure 3.10 shows the classification of subjects in both groups using the significant parameters found in stand-bend, walking, and turning phases respectively. Stars show the training points while circles show the test subjects. For the walking phase, the subject displaying a longer time duration, with a lower acceleration RMS value, is at greater risk of falling. For turning phases, the longer the duration and the lower the angular velocity amplitude are, the greater risk of falling. For stand-bend phase, as observed from Figure 3.8, the subjects could not be clearly classified into two groups. According to the Figure 3.9 and Figure 3.10, by using the k-NN algorithm, the test subjects could be accurately classified into groups following the training data in walking and turning phases.

This study demonstrated how a single wearable inertial sensor could be used to classify the subjects in terms of fall risk by using standard physical assessment; TUG test. We classify the subjects using dual parameters, instead of using only the time parameter. By using the angle signal for phase determination, subject movement could be accurately characterized during the sit-stand and stand-sit phases. Most notably, this enables distinguishing of the phase transition from the sit-stand phase to the walking phase. This may reduce the need for subjects to use many sensors. As a result, a therapist could handle the experiment more easily with simple sensor attachment.

78 parameters were gathered from 3 signal types in 3 directions. 44 parameters were reported to have been significantly different. Figure 3.1 summarises that subjects in the HFR group took longer to complete each phase as well as to complete the whole test. This result showed the same trend as observed in previous research Podrichard et. al,shumway et. al,Higashi et. al and Barry et.al also agrees well with current clinical practice. For the sit-stand phase, there was no significant difference found using the time parameter for demarcating fall risk groups. The separation into two detailed phases: sit-bend and bend-stand, provided better results. Figure 3.2 indicates that, from the comparison between HFR and LFR in terms of time parameters, there was very high p-value (p=0.85) in sit-bend phase compared with that in bend-stand phase (p=0.08). This suggests that high p-value (p=0.25) in sit-stand phase may have been contributed by sit-bend phase. As a result, it is appropriate if the bend-stand phase is used to present the sit-stand phase. This is evident in Figure 3.2. Unfortunately, lower p=0.08 in the bend-stand phase still does not satisfy $\alpha < 0.05$; however, it is

shown that the component in the sit-stand phase has a tendency to differentiate the two groups. A correlation between time taken to complete each phase and the total time taken to complete the TUG test was also observed. A low correlation was found in the bend-stand phase, while other phases had high correlation, with the walking phase achieving the highest value of r. This findings might indicate that time taken depended on the individual and could not be used as a parameter for evaluating the fall risk. Moreover, classifying the subjects using only the time parameter will not reveal the movement activities in each phase. To investigate this issue further, comparisons between the two groups were carried out using other parameters. As summarised in Table 1, there were significant differences in bend-stand and stand-bend phases using the RMS value of acceleration signal in the vertical direction. As well as for walking phases, significant differences were found in walking in all directions using the RMS value in the acceleration signal. As shown in Figure 3.6, the RMS value in LFR was higher than in HFR subjects in all phases. We consider that the rigid movement by HFR elderly might have resulted in a lower RMS value. This might explain that the LFR subjects varied more during bend-stand and stand-bend movements than the HFR subjects. During the turning phases, subjects in the LFR group had a higher amplitude of angular velocity, as presented in Figure 3.7 . The higher amplitude may signify that the subjects in the LFR group moved more actively than the subjects in the HFR group. This observation is evident when the LFR group produced a larger change in the angular displacement over time. Significant differences in relevant parameters were found in all phases of the respective activities. Our technique circumvents the limitations of the previous approach presented by Higashi et. al leads to an improved result.

Using dual parameters applied with the k-NN algorithm, the HFR and LFR could be classified into two different groups within the test subjects, which were accurately categorized into their respective groups in the walking and turning phases. Nevertheless, in bend-stand, the two groups were not classified appropriately. In contrary to the dynamic motion in walking and turning phases, the static movement in the sit-stand and stand-sit phases might have contributed to these results. In the case of walking phases, RMS values of acceleration signal in the vertical direction along with the time parameter can reasonably describe the subject activities. Significant differences between the HFR and LFR in terms of amplitude of angular velocity signal in the yaw direction plotted against the time parameter could be used to classify the subject activities. The classification using 2 parameters limiting the use of parameters in classifying the elderly. As we collected 78 parameters with 44 are shown to have significant different, it is interesting if it is possible to see the effects of all parameters to the subjects at one time. In addition, within of these parameters, there are it is better if we can choose the parameters that most greatly influence the data. For this pupose, we applied a statistical technique handling with multiple variable.

3.3.2 Principle Component Analysis

Choosing the parameter to be used in classifying the fall risk among elderly is one of the issue in this study. In visualising the differences between both groups, using only one parameter and two parameters from gathered parameters do not contribute the whole story of the data. We decided to apply the multivariate analysis to the data in hopes of providing better classification compared to k-NN.

In all parameters, there are redundancy between data occurred. In order to simplify the data, yet still get the overall picture of the data, we use the principal component analysis to reduces the redundant features. The PCA also a techniques that could indicate which attributes contribute the most to the group differentiation.

From PCA,the importance of components gathered are as below in 38 of principal components.

Principal component	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Standard deviation	92.1254	58.8186	41.12302	32.0611	28.42016	26.48515	19.4766
Proportion of Variance	0.4946	0.2016	0.09854	0.0599	0.04707	0.04088	0.0221
Cumulative Proportion	0.4946	0.6962	0.79470	0.8546	0.90166	0.94254	0.9646

Principal component	PC8	PC9	PC10	PC11	PC12	PC13	PC14
Standard deviation	17.17276	10.28761	9.19015	7.6357	5.0753	4.23123	3.16847
Proportion of Variance	0.01718	0.00617	0.00492	0.0034	0.0015	0.00104	0.00058
Cumulative Proportion	0.98183	0.98799	0.99291	0.9963	0.9978	0.99886	0.99944

Principal component	PC15	PC16	PC17	PC18	PC19	PC20	PC21
Standard deviation	2.29182	1.34403	1.10845	0.73451	0.66706	0.33640	0.2864
Proportion of Variance	0.00031	0.00011	0.00007	0.00003	0.00003	0.00001	0.0000
Cumulative Proportion	0.99975	0.99985	0.99992	0.99996	0.99998	0.99999	1.0000

Principal component	PC22	PC23	PC24	PC25	PC26	PC27	PC28
Standard deviation	0.1948	0.1672	0.1499	0.1145	0.1086	0.06951	0.06138
Proportion of Variance	0.0000	0.0000	0.0000	0.0000	0.0000	0.00000	0.00000
Cumulative Proportion	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Principal component	PC29	PC30	PC31	PC32	PC33	PC34	PC35
Standard deviation	0.04216	0.03735	0.02493	0.02152	0.01748	0.01205	0.009445
Proportion of Variance	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Cumulative Proportion	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Principal component	PC36	PC37	PC38
Standard deviation	0.005595	0.003914	8.472e-15
Proportion of Variance	0.000000	0.000000	0.000e+00
Cumulative Proportion	1.000000	1.000000	1.000e+00

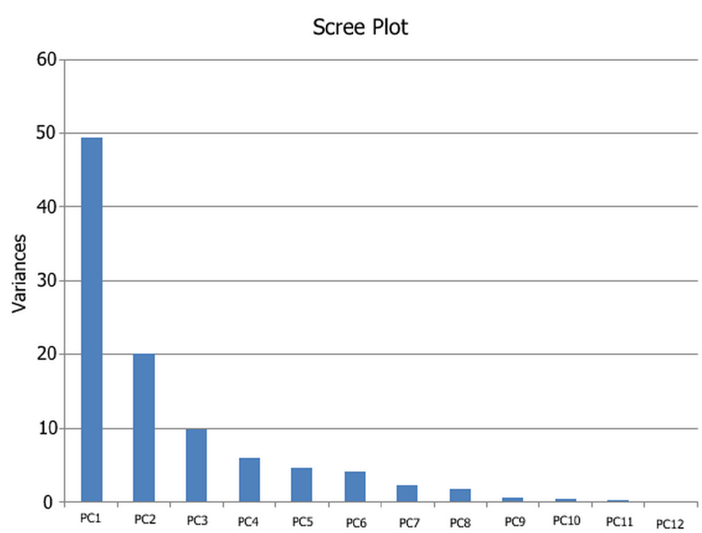


Figure 3.11: A scree plot of variances explain by the principal components.

The first component contribute 49.46% of the variance to the whole data. The PC1 is insufficient to model the systematic variation of the data set. Thus the second component is considered. The PC2 contribute 20.16%. A barplot of each component's variance in Figure 3.11 shows how the first two components influence the data. The PC1 and PC2 have most adequate for classification which discover about 70% of the variance in the data. In general, it assumes that two components explain a sufficient amount of the variance to provide a meaningful visual representation of the subjects and parameters.

Table 3.2: Rank by the most important parameters using new variable of Principal Component 1 and Principal Component 2.

Rank	PC1		PC2		Rank	PC1		PC2	
	Score	Parameter	Score	Parameter		Score	Parameter	Score	Parameter
1	0.55172	P16	0.81900	P75	19	0.00065	P48	-0.00095	P60
2	0.48550	P75	0.01089	P59	20	0.00061	P28	-0.00190	P55
3	0.40812	P15	0.00884	P33	21	0.00061	P45	-0.00200	P77
4	0.32078	P41	0.00545	P64	22	0.00055	P46	-0.00216	P78
5	0.24929	P73	0.00506	P50	23	0.00054	P43	-0.00262	P61
6	0.17465	P74	0.00158	P69	24	0.00044	P44	-0.00524	P56
7	0.15226	P51	0.00129	P63	25	0.00043	P29	-0.01061	P53
8	0.14891	P38	0.00105	P49	26	-0.00047	P67	-0.01633	P51
9	0.12156	P37	0.00071	P65	27	-0.00074	P65	-0.01667	P54
10	0.10842	P52	0.00057	P67	28	-0.00143	P69	-0.03265	P52
11	0.08617	P54	0.00010	P45	29	-0.00248	P63	-0.09801	P37
12	0.07850	P53	-0.00001	P43	30	-0.00311	P61	-0.15244	P41
13	0.07142	P33	-0.00003	P46	31	-0.00400	P60	-0.17521	P15
14	0.06272	P49	-0.00009	P28	32	-0.00622	P56	-0.18188	P16
15	0.05117	P50	-0.00012	P44	33	-0.00799	P55	-0.22961	P38
16	0.00419	P77	-0.00015	P29	34	-0.00985	P64	-0.26356	P73
17	0.00309	P78	-0.00018	P47	35	-0.01971	P59	-0.32925	P74
18	0.00086	P47	-0.00031	P48					

The rank listed in this Table 3.2 which shows the most and the least important parameters ranked from 1 to 35 for both principle components. From 44 significant parameters, 35 parameters were selected with 9 time parameters were removed from the data. From the very beginning of this research, we divide all subjects into HFR and LFR using the total time parameters. To avoid the high influence by the time parameters, we remove all time parameters to see whether other parameter could accurately classify the elderly correctly into their respective groups. As we can see that the most important parameter in PC1 is the P16(amplitude of angular velocity signal during turn 2 phase in yaw direction). Meanwhile, the most important parameter in PC2 is the P75(cadence parameter in turn 1 phase) shown in Table 3.2.

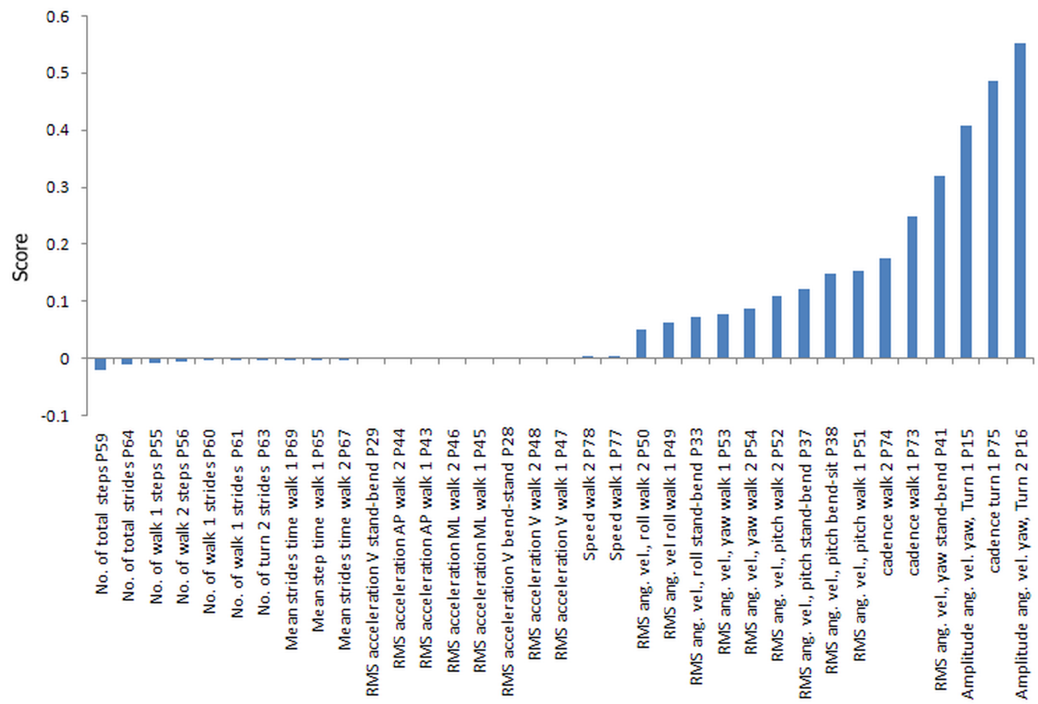


Figure 3.12: The most important parameter in PC1

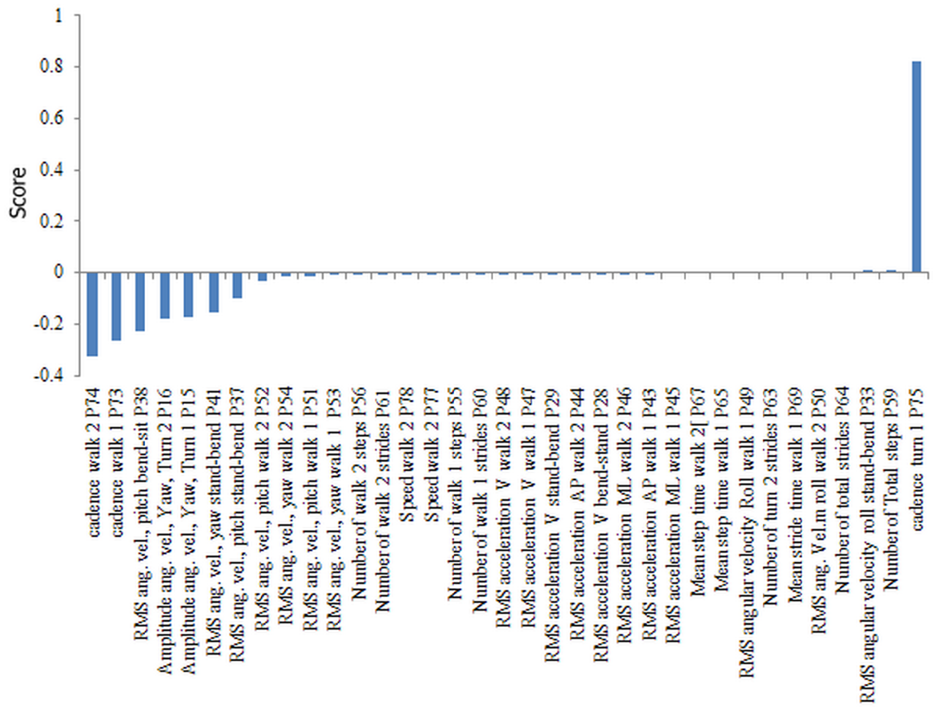


Figure 3.13: The most important parameter in PC2

Figure 3.12 and Figure 3.13 are the rank of the most important parameters PC1 and PC2 respectivelyin barplot. Referring to the ranking illustrated by the PC1, the most important parameters were listed as P16, P75,, P15, P41, P73, P74, P51, P38, P37, P52, P54, P53, P33, P49 and P50 in positive score, while the P59, P64, P55, P56, and P60 are the most important parameters in negative value score. On the other hand, the parameters were rank in using the PC2 as the P75 presented the most important parameter with very high positive value, meanwhile P74, P73, P38, P16, P15, P41, P37, P52, P54, P51 and P53 were listed as the most important parameters in negative value score.

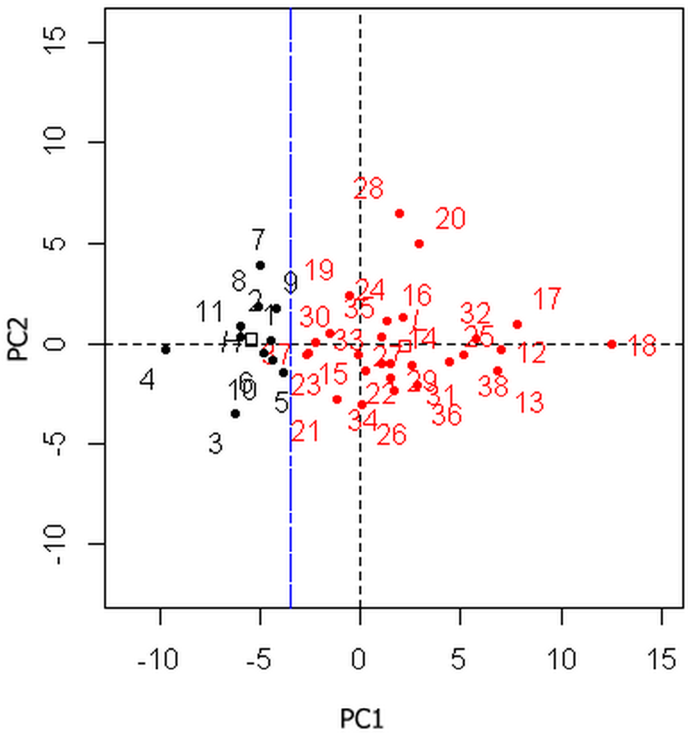


Figure 3.14: PCA score plot of the two first principal component.

The PC1 and PC2 were derived and defined a plane. By projecting all the observation onto this two lower dimensional sub-space and plotting the results, it is possible to visualize the pattern of 38 subjects using 35 parameters. Figure 3.14 shows the distribution of 38 subjects in the PC1 and PC2 plane. The co-ordinate values of this planes called scores, and plotting of such projected is known as score plot. The graph distributions forming into two group, describes a convincing illustration that encourage for a good classification result. As for the PC1, the negative value influence the classification for subject in HFR group, while the positive value influence the classification into LFR group. In the meantime, the PC2 do not give any effect in classifying HFR and LFR. As seen in the figure, the HFR and LFR can be almost 100% accurately classified into their respective groups. As illustrated in the figure, the classification was contributed by the PC1, while the PC2 did not play a role in classifying the subjects into groups. Therefore, the parameters listed in the PC1 were chosen to be used in classifying the subjects.

Discriminant Analysis-PCA

In order to perform the group discrimination in multiple analysis, the linear discriminant analysis was applied to the data. As discussed previously, based on how the parameters influence the data, parameters were ranked using PCA. From 35 parameters, the unimportant parameters or noisy from the data that shows small contribution to the PC1 were removed and 20 important parameters were chosen for the classification purpose in LDA. It should, however, be noted that LDA works when the measurements made on independent variables for each observation are continuous quantities. It is unacceptable if using dependent variable in the data that may effect the output of the final result. As a result, eighteen parameters were identified as the most importance parameters chosen from principle component 1 with two parameters; P59 (total number of step) and P64 (total number of stride) were required to be removed.

Table 3.3: Number of Observations and Percent Classified into Fall Risk using LDA with Parameters selected from PC1.

Groups		HFR	LFR	Total
HFR	Number of observation	7	4	11
	Percent classified into fall risk	63.64	36.36	100
LFR	Number of observation	5	22	27
	Percent classified into fall risk	18.52	81.48	100
Error rate		0.3636	0.1852	0.2744

Table 3.4: Number of Observations and Percent Classified into Fall Risk using LDA with Parameters selected from PC1.

Groups		HFR	LFR	Total
HFR	Number of observation	9	2	11
	Percent classified into fall risk	81.81	18.18	100
LFR	Number of observation	7	20	27
	Percent classified into fall risk	25.93	74.07	100
Error rate		0.1818	0.2593	0.2205

Eighteen parameters in the PC1 were selected and LDA were performed. The classification result and its error rate were summarized in Table 3.3. Four of nine subjects from HFR were misclassified into LFR group, meanwhile five of 22 subjects from LFR were misclassified. Three parameters from negative side of the graph were identified to have very small value contribute least importance parameters. In order to reduce the error rate in classifying subject into HFR and LFR using LDA, those three parameters were removed and LDA applied to the data with only using 15 parameters. As a results, two of eleven HFR were misclassified into LFR group, seven of 22 subjects from LHR were misclassified into HFR group. The average recognition rate were increase from 72% to 77%, when we reduce those parameters from the analysis. However, the misclassified subjects in LFR were increase. Even so, the false positive result in the upper analysis in Table 3.3 are higher compared to result in Table 3.4. A false negative is a test result that indicates a subject does not have fall risk, but the person actually does have risk. This situation endangering the HFR elderly. It is better to have the false positive result in the lower table than the false negative result in Table 3.3 for fall risk prediction. As a result, 15 parameters from were selected to be the most influence parameters listed in Table 3.5.

Table 3.5: The most important parameters selected using PC1 in PCA.

	Parameters	Signals	Directions	Phases
P16	Amplitude	Angular Velocity	Yaw	Turn 2
P75	Cadence			Turn 1
P15	Amplitude	Angular Velocity	Yaw	Turn 1
P41	RMS	Angular Velocity	Yaw	Stand bend
P73	Cadence			Walk 1
P74	Cadence			Walk 2
P51	RMS	Angular Velocity	Pitch	Walk 1
P38	RMS	Angular Velocity	Pitch	Bend sit
P37	RMS	Angular Velocity	Pitch	Stand bend
P52	RMS	Angular Velocity	Pitch	Walk 2
P54	RMS	Angular Velocity	Yaw	Walk 2
P53	RMS	Angular Velocity	Yaw	Walk 1
P33	RMS	Angular Velocity	Roll	Stand bend
P49	RMS	Angular Velocity	Roll	Walk 1
P50	RMS	Angular Velocity	Roll	Walk 2

The most important parameter is the P16 which is the amplitude of angular velocity signal in yaw direction during turn 2 phase. And it is followed by the P75 which is the cadence parameter during turn 1 phase. The third most important parameter also from turning phase; which is the amplitude of angular velocity signal in yaw direction during turn 1 phase.

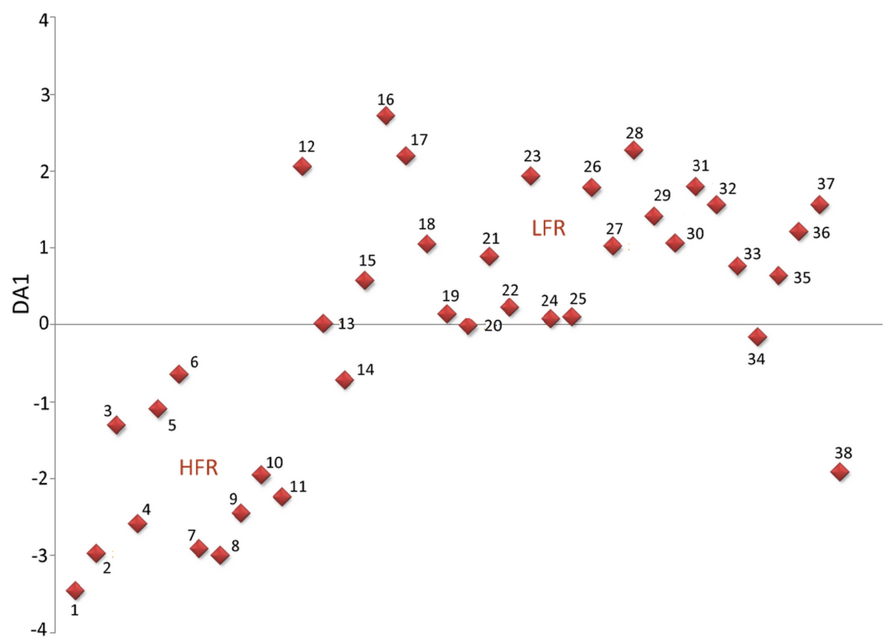
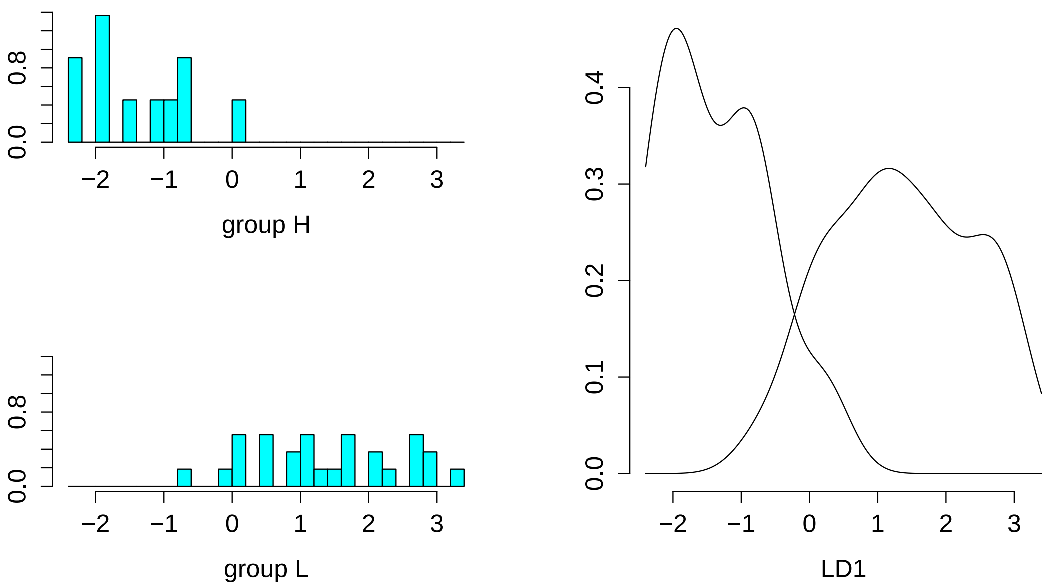


Figure 3.15: A classification between HFR and LFR groups
in using chosen parameters by PCA.

In order to discriminate elderly between LFR and HFR, LDA were performed. Classification result were plotted in scatter plot and illustrated in Figure 3.15. It clearly can be seen that the two groups were separated correctly by a single new composite variable LD1, variable which combines using the 15 parameters selected in PCA.



(a) (b)

Figure 3.16: Discriminant distribution between HFR and LFR using parameters chosen from PCA.

Using the 15 parameters, the LD1 can clearly separate the two group, with the discriminant distribution displayed in the Figure 3.16 (b) shows normal distribution of 'discriminant scores. The degree of overlap between the discriminant score distributions can be used as a measure of the success of the technique and some overlap between HFR and LFR group can be observed in the figure.

3.3.3 Random Forest

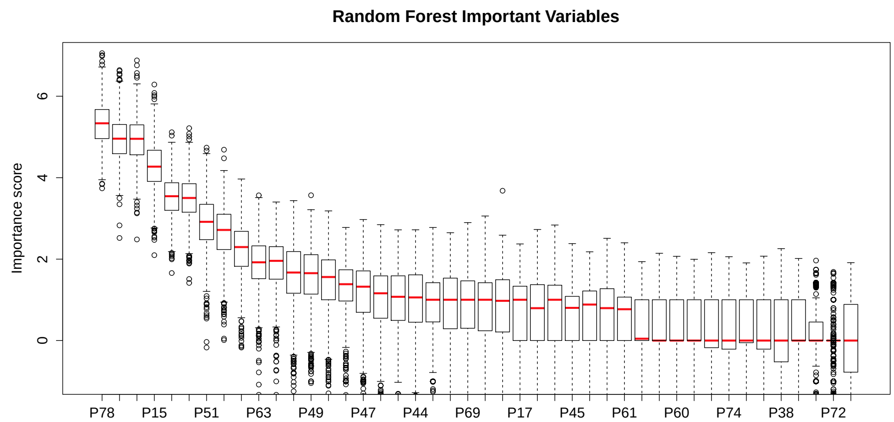
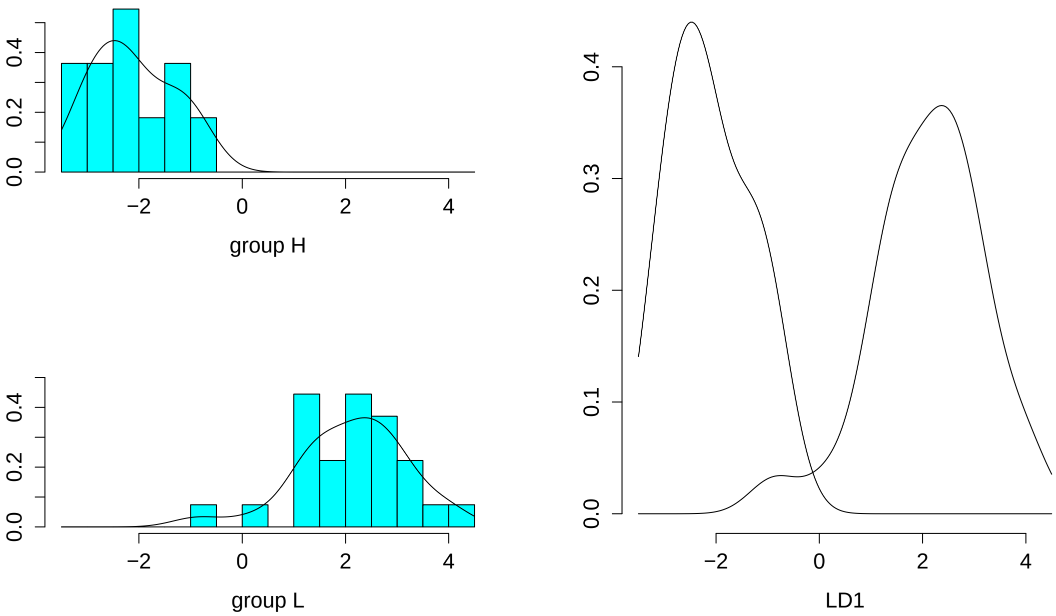


Figure 3.17: Random Forest Analysis: The Importance score bar plot of all parameter excluding the time parameters(ntree=200).

The bar plot in Figure 3.17 illustrate the behaviour of parameter importance in classifying the fall risk among elderly using all data except the eleven parameters of time. The variable important figure were obtained for data n=38 and p=67, parameter ntree are set to 200, while mtry are set as 1/3 of the 67 parameters as training, and OOB as test data with 1000 trials. The global picture is the following: it can be seen that 9 parameters were shown to have higher importance of score which is higher than 2, 20 moderately important parameters with importance score 2 and less to zero, and the others of small importance. For the less important parameter it shown that the box-plots are larger. and the mean red line is not positioned in the center of the box. The higher the important score, the important parameter is. From the boxplot, it illustrated that 31 parameters have score more than 0. We selected the 31 parameters as the most important parameters in random forest analysis. In order to use the selected parameter to classify the elderly into HFR and LFR, we applied the data with DA.



(a) (b)

Figure 3.18: Discriminant distribution between HFR and LFR using parameters chosen from random forest analysis.

Table 3.6: Number of Observations and Percent Classified into Fall Risk using Random Forest.

Groups		HFR	LFR	Total
HFR	Number of observation	9	2	11
	Percent classified into fall risk	81.82	18.18	100
LFR	Number of observation	0	27	27
	Percent classified into fall risk	0	100	100
Error rate		0.1818	0	0.091

We classified the subject into both group using 31 selected parameter. However, due to DA limitation which the parameters need to be independent variable, we removed 8 parameters from chosen 31 parameters. Using the 23 selected parameters by random forest analysis, the LD1 can clearly separate the two group, with the discriminant distribution displayed in the Figure 3.18 reduced the overlap between HFR and LFR group compared to the classification using selected parameters from PCA in Figure 3.16 . Table 3.6 shows the classification error rate. It is indicated that there are only 2 LHR subject were misclassified to LFR group and no LFR subject were misclassified. Although there are no false positive result, There are 2 false negative occurred using the random forest, same result as in PCA with the average recognition is 90.91%.

Table 3.7: The most important parameters selected using random forest.

	Parameters	Signals	Directions	Phases
P78	Speed			Walk 2
P77	Speed			Walk 1
P16	Amplitude	Angular Velocity	Yaw	Turn 2
P15	Amplitude	Angular Velocity	Yaw	Turn 1
P51	RMS	Angular Velocity	Pitch	Walk 1
P52	RMS	Angular Velocity	Pitch	Walk 2
P43	RMS	Acceleration	Antero posterior	Walk 1
P50	RMS	Angular Velocity	Roll	Walk 2
P49	RMS	Angular Velocity	Pitch	Walk 1
P48	RMS	Acceleration	Vertical	Walk 2
P53	RMS	Angular Velocity	Yaw	Walk 1
P47	RMS	Acceleration	Vertical	Walk 1
P44	RMS	Acceleration	Antero posterior	Walk 1
P46	RMS	Acceleration	Medio lateral	Walk 2
P65	Mean step time			Walk 1
P69	Mean stride time			Walk 1
P73	Cadence			Walk 1
P41	RMS	Angular Velocity	Yaw	Stand-bend
P14	Amplitude	Angular Velocity	Pitch	Stand-sit
P37	RMS	Angular Velocity	Pitch	Stand-bend
P29	RMS	Acceleration	Vertical	Stand-bend
P45	RMS	Acceleration	Medio lateral	Walk 1
P33	RMS	Angular Velocity	Roll	Stand-bend

As a result in random forest, 23 most important parameters were selected as per listed in Table 3.7. The most important parameter is the P78 which is the speed parameter during walk 2 phase. And it is followed by the P77 which is the speed parameter during walk 1 phase. The third and forth most important parameter also from turning phase; which is the amplitude of angular velocity signal in yaw direction during turn 2 phase(P16) and amplitude of angular velocity signal in yaw direction during turn 1 phase(P15) as also listed in the Table 3.5.

Chapter 4

Discussion

> Rasulullah saw said: "Whoever acts to be heard and seen, God will cause his falsity to be heard and seen".
>
> Bukhari, Muslim

4.1. Quantitative Analysis

This study demonstrated how a single wireless inertial sensor could be used to classify the subjects in terms of fall risk by using standard physical assessment TUG test. We classify the subjects using dual parameters and multi-parameters, to objectively quantify and provide a quantitative evaluation of falling risk, and harnessing the quantitative information well beyond simply the time taken to perform the test. Our finding in this study summarizes that the traditional TUG measured with a stopwatch was not a sensitive tool to detect gait and posture abnormalities in elderly. Instead of using many sensors, this study use a single sensor in attached at waist dorsally in determining the phase transition. This may reduce the need for subjects to use many sensors. As a result, a therapist could handle the experiment more easily with simple sensor attachment. By using the angle signal for phase determination, subject movement could be accurately characterised in phases. Most notably, this enables distinguishing of the phase transition from the sit-stand phase to the walking phase. By assessing a wide variety of spatial and temporal components in each phases, we uncovered mobility deficits that were not evident with stopwatch in phases.

78 parameters were gathered from three signal types in three directions. 44 parameters were reported to have been significantly different. Figure 3.1 summarises that subjects in the HFR group took longer to complete each phase as well as to complete the whole test. This result showed the same trend as observed in previous research [1, 5–7], and also agrees well with current clinical practice. For the sit-stand phase, there was no significant difference found using the time parameter for demarcating fall risk groups. The separation into two detailed phases: sit-bend and bend-stand, provided better results. Figure 3.2 indicates that, from the comparison between HFR and LFR in terms of time parameters, there was very high p-value ($p = 0.85$) in sit-bend phase compared with that in bend-stand phase ($p = 0.08$). This suggests that high p-value (p=0.25) in sit-stand phase may have been contributed by sit-bend phase. As a result, it is appropriate if the bend-stand phase is used to present the sit-stand phase. This is evident in Figure 3.2. Unfortunately, lower $p = 0.08$ in the bend-stand phase still does not satisfy α <0.05; however, it is shown that the component in the sit-stand phase has a tendency to differentiate the two groups. A correlation between time taken to complete each phase and the total time taken to complete the TUG test was also observed. A low correlation was found in the bend-stand phase, while other phases had high correlation,with the walking phase achieving the highest value of r. This findings might indicate that time taken depended on the individual and could not be used as a parameter for evaluating the fall risk. Moreover, classifying the subjects using only the time parameter will not reveal the movement activities in each phase. To investigate this issue further, comparisons between the two groups were carried out using other parameters. As summarised in Table 3.1, there were significant differences in bend-stand and stand-bend phases using the RMS value of acceleration signal in the vertical direction. As well as for walking phases, significant differences were found in walking in all directions using the RMS value in the acceleration signal. As shown in Figure 3.6, the RMS value in LFR was higher than in HFR subjects in all phases. We consider that the rigid movement by HFR elderly might have resulted in a

lower RMS value. This might explain that the LFR subjects varied more during bend-stand and stand-bend movements than the HFR subjects. During the turning phases, subjects in the LFR group had a higher amplitude of angular velocity, as presented in Figure 3.7. The higher amplitude may signify that the subjects in the LFR group moved more actively than the subjects in the HFR group. This observation is evident when the LFR group produced a larger change in the angular displacement over time. Significant differences in relevant parameters were found in all phases of the respective activities. Our technique circumvents the limitations of the previous approach presented by Higashi et al. that leads to an improved result.

4.2. Classification Analysis

Previous researchers had address the problem of fall risk among elderly. Few researchers analysed the fall risk quantitatively using the sensors. However the classification using only one parameter at one time limit the evaluations. In this study we used four types of classification in detecting to which groups is elderly belonged to HFR or LFR. We first attempt to use dual parameters applied with the k-NN algorithm. Instead of evaluating fall risk using time parameter only, therapist could use the information given by the other parameters, especially involving spatial parameters. The HFR and LFR could be classified into two different groups within the test subjects, which were accurately categorised into their respective groups in the walking and turning phases. In the case of walking phases, RMS values of acceleration signal in the vertical direction along with the time parameter can reasonably describe the subject activities. Significant differences between the HFR and LFR in terms of amplitude of angular velocity signal in the yaw direction plotted against the time parameter could be used to classify the subject activities. Nevertheless, in bend-stand, the two groups were not classified appropriately. In contrary to the dynamic motion in walking and turning phases, the static movement in the sit-stand and stand-sit phases might have contributed to these results. An alternative approach is necessary with the intention of enhancing the classification technique. Using k-NN analysis, we could evaluate elderly whether they have falling risk or not using only two parameters.

Fall risk classification using 2 parameter limit the classification only using parameters. As we collected 78 parameters with 44 are shown to have significant different, it is interesting if it is possible to see the effects of all parameters to the subjects at one time. Therefore we applied a statistical technique handling with multiple variable. Applying PCA to the significant data improves the classification method. Instead of using only selected two parameters at one time, multiple parameter were used. using 35 parameters, PC1 could clearly separate the elderly into HFR and LFR. The distributions of subjects into two groups as shown in Figure **??** encourage for a good classification results using PC1. Among all 35 significant parameters, 15 most important parameter were selected from PC1. According to the result from Table 3.5, the most three important parameters from in classifying the elderly was in turning phases; p16, P75 and P15. Evidence from this, it could be conclude that evaluation using turning activity give better results in determining the fall risk among elderly. By using PCA, we can determine a subject's belonging to a group or LFR or HFR very well. However, the prime difference between LDA and PCA is that PCA does more of feature classification and LDA does data classification. Therefore, we decided to used LDA in classifying the subjects into their respective groups. The result was displayed in Chapter three. For comparison, we also use the random forest that provides more accuracy in classifying the HFR and LFR. This evident by the lower error rate shown in RF comparing to using PCA and LDA. In addition, we do not have to choose the best data first before applying to the random forest to ensure a good results as we need to choose in PCA and LDA. As a result using RF, 23 most important parameters were selected as per listed in Table 3.7. The different method applied in RF; using a method that construct a collection of decision trees with controlled variation tree, given almost the same selection of important parameters. Although the most important parameters was P78 and P77 were chose in RF analysis, the third and forth parameters chosen are P16 and P15 as per selected using the PCA analysis. It is apparent that both analysis exhibit that the P16 and P15 are listed in the most important parameter list. Combining this results, it may be able to conclude that the most influence spatial parameter to differentiate the HFR and LFR were found in phases using PCA and RF are:

1. Sit-stand(stand bend) = no significant parameter
2. Walking = RMS of Angular Velocity in pitch direction (P51 and P52)
3. Turning = Amplitude of Angular Velocity in yaw direction (P15 and P16)
4. Stand-sit (stand-bend) = RMS of Angular Velocity in Yaw direction
5. For the sit-stand phase, the significant different were found using the RMS of acceleration parameter in vertical direction, using the t-test analysis.

4.3. Clinical interpretation

From our approach, we can make further discussion for specific subject by using the parameters gathered in each phase. The subjects could not only be classified as HFR and LFR; moreover, therapists could detect which activity might lead the subject to fall. By using time parameter, four subjects were chosen as examples, as shown in Table 4.1.

Table 4.1: High fall risk subject in terms of different weaknesses using time parameters.

Sub	Sit-bend[s]	Bend-stand [s]	Sit-stand [s]	Walk 1[s]	Turn 1[s]	Walk 2[s]	Turn 2[s]	Stand-bend[s]	Bend-stand[s]	Stand-sit[s]	Total[s]
A	0.93	0.86	1.79	3.95	3.46	3.36	1.97	1.58	1.33	2.91	16.27
B	0.36	0.44	0.8	5.51	1.93	3.91	1.07	1.43	1.22	2.65	15.2
C	0.91	1.62	2.53	2.33	2.03	3.85	1.56	2.02	1.35	3.37	14.52
D	0.4	0.67	1.07	5.63	2.3	4.95	1.63	1.47	1.15	2.62	17.25

All four subjects had been classified as HFR subjects. As shown in Table 4.1, the total duration for test completion for all subject was over 13.5 seconds. Using only the total duration, a therapist could understand that these subjects should be classified as at HFR. However, using analysis by phases, performance in each activity is revealed. For instance, the results obtained for subject A, showed good performance in sit-stand and stand-sit, but not in turning phases. Meanwhile, subject B took longer to complete the walking phase, but had good performance in other phases. Different results were recorded for subject C: the longer time taken in the stand-sit phase indicates a bad performance in that phase. The longer time required in the walking phases by subject D indicated bad performance in walking, but good performance in other phases. A therapist could use these data to train or improve a subject's performance. A therapist might train to subject A to improve performance in the turning phase, subject B to improve walking, subject C to improve sit-stand and stand-sit, while walking training would be essential for subject D.

Table 4.2: High fall risk subject in terms of different weaknesses using spatial parameters.

Sub	Stand-bend (RMS-AV yaw)	walk 1 (RMS-AV pitch)	Walk 2 (RMS-AV pitch)	Turn 1 (AMP-AV yaw)	Turn 2 (AMP-AV yaw)
A	71.34	13.85	14.32	95.39	108
B	79.35	22.44	19.1	90.93	188.9
C	75.13	19.5	17.23	104.1	183.9
D	62.16	18.49	16.47	115.3	121.8
Average	55.3	19.38	19.73	107.09	123.38

Using other than time parameter may be more informative if we could provide spatial parameter to therapist in evaluating the fall risk among elderly. As per discussed in previous section, parameter RMS value of angular velocity in yaw direction are the most influence parameter in evaluating the elderly in stand-bend phase; which represent the stand-sit phase. The RMS of angular velocity in pitch direction are the most important parameters in evaluating the walking activity, whether the subject prone to fall or not. Meanwhile, for turning phase, the most influence parameter are the RMS value of angular velocity in yaw direction. Using these parameter, performance in each activity were observed as detailed in Table 4.4. For comparison, we use the same subjects, A,B,C and D as in Table 4.1. It can be observed that subject A have bad performance in turning phases due to lower RMS value of angular velocity in yaw direction. Considering to the difficulty during turning activity, subjects rotates more slowly and produce lower amplitude of angular velocity signal in yaw direction. If the same subject necessitate their body turn faster with bigger angle per second, the subject will have risk to fall since the turning ability of that subject to turn are lower in terms of this parameter. Similar result was observed in subject B in using spatial parameter in Table 4.1 and Table 4.3 showing that the subject B have bad performance in walking phase with higher RMS value in pitch direction. During standing subjects keep their body's center of mass(COM) safely within the base of support. However, when subject wish to walk for one step or more, the criterion of balance are remarkably changed. Now the subject required to move their body outside the base support and yet prevent the falling. In order to stabilize their body, subjects try to lowering their COM, and their body moved laterally during the walking phase. As a results, the subject will have higher RMS value of angular velocity signal in pitch direction. Meanwhile, subject C and subject D do not show any problems in phases activities, although the subject was grouped as the HFR using the total time evaluation.

Table 4.3: Low fall risk subject in terms of different weaknesses using time parameters.

Sub	Sit-bend[s]	Bend-stand [s]	Sit-stand [s]	Walk 1[s]	Turn 1[s]	Walk 2[s]	Turn 2[s]	Stand-bend[s]	Bend-stand[s]	Stand-sit[s]	Total[s]
E	0.82	0.33	1.15	2.47	1.23	2.64	0.79	1.19	1.04	2.23	9.57
F	0.48	0.6	1.08	2.58	0.82	2.72	0.86	1.04	1.02	2.06	9.32
G	1.28	0.59	1.87	3.09	1.82	3.07	1.34	1.25	1.41	2.66	13.21
H	0.63	0.47	1.1	2.46	1.6	2.85	0.93	0.76	0.81	1.57	10

As can be seen in Table 4.3, four subjects from LFR group were selected. All four subjects had been classified as LFR subjects. The total duration for test completion for all subject was less than 13.5 seconds. Using only the total duration, a therapist could understand that these subjects should be classified as at LFR. In general, we can see that all subjects, E,F,G and H do not have any problems in any phases referring to the time parameters in phases. However, using the spatial parameters in evaluating the fall risk, we can see that the subject G have lower RMS value in angular velocity in yaw direction during stand-bend phase. Although subject G was predicted do not have risk of falling using the time parameters, this subject was determined having a problem during stand-sit activities and this subject also might have problem during sit-stand activities, and prone to fall. The false negative result exhibit from the time parameters endanger the subject G during this activity. Furthermore, using the spatial parameter, therapist might use this information to improve the subject G for stand-sit or stand-sit phase.

Table 4.4: Low fall risk subject in terms of different weaknesses using spatial parameters.

Sub	Stand-bend (RMS-AV yaw)	walk 1 (RMS-AV pitch)	Walk2 (RMS-AV pitch)	Turn 1 (AMP-AV yaw)	Turn 2 (AMP-AV yaw)
E	95.61	40.71	39.03	185.8	164.7
F	130.94	16.44	17.21	154.1	221.3
G	69.32	25.08	29.22	150.1	197.5
H	112.08	41.91	35.09	169.9	211.6
Average	97.08	46.19	40.44	165.88	200.14

In general, using the temporal and spatial parameters could classify the fall risk among elderly. In addition, using spatial parameter, therapist could use the information revealed by the sensor and pinpoint the problem suffer by elderly. Therapist also may use the information in improving the therapy and focusing the potential problem.

4.4. Subject - parameter mapping

Apart from being able to choose the most important parameters, the most important use of PCA is indeed to represent a multivariate data as a low-dimensional plane, such that an overview of the data could be obtained. The overview may reveal groups of observations, trends, and outliers. This overview also uncovers the relationships between the observations an variables, and among the variables themselves.

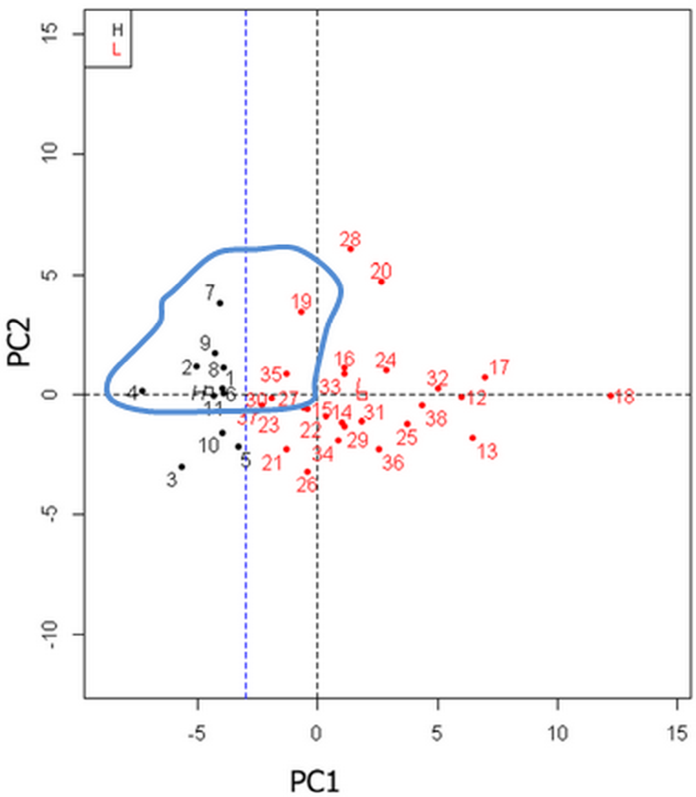


Figure 4.1: PCA score plot of the two first principal component.

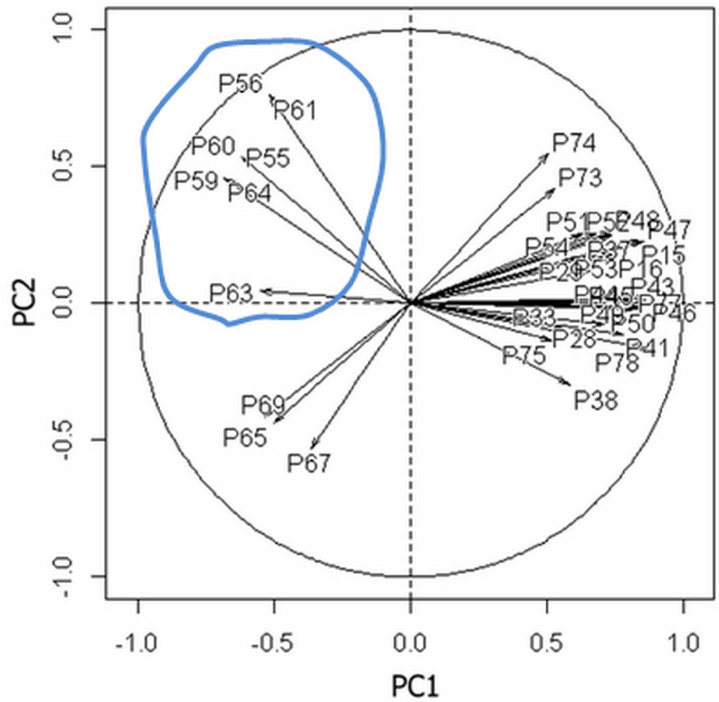


Figure 4.2: PCA loading plot of the two first principal component.

The pattern seen among the subjects distributions were influenced by which parameters could be identified by the principal component scores and loadings. Figure 4.1 provides a map how the 38 subjects relate to each other. All subjects is characterized by two values, one along the PC1 and another along the PC2. Subjects close to each other have similar properties, whereas those far from each other are dissimilar. The subjects from HFR close to each other in the left side of the graph, while the subject from LFR gathered in the right side of the graph. The scores of the PC are accompanied by the corresponding loadings. A scatter plot of the loadings of the first component versus the loading of the second component is shown in Figure 4.2. This plot indicates the relationship between all variables at the same time. Variables contributing similar information are grouped together, that is, they are correlated. P28(RMS of acceleration signal in vertical direction during the stand-bend phase) and P38(RMS of angular velocity signal in pitch direction during the bend-sit phase) are example of two parameters which are positively correlated. When the numerical value of one variable increases or decreases, the numerical value of other variable has tendency to vary in the same way. When the parameters are inversely correlated they are positioned on opposite side of the plot origin, in diagonally opposed quadrant. For instance, parameter P63 (Number of strides during turn 2 phase) and the parameter P61 (Number of strides during walk 2 phase) are inversely correlated, meaning when the RMS increases, the number of strides will decreases, and vice versa. In addition, the distance of the variable location to the origin in the distributions also deliver information. The stronger impact that parameter has on the model if it is plotted further away from the plot origin. Using this information, therapist might could see the pattern of the subject in term of their disease. As for example, if the subject in quarter 1 in Figure 4.1 are subjects from some related disease, the properties shown in the variable map in Figure 4.2 is the parameters or properties that influence the group of those elderly. Using this result, therapist could predict the effect of the disease that elderly might suffers to their gait and fall risk factors.

4.5. Falls Mechanism and Parameter's Relationship

Falling mechanism described by [43] is that the subject will experience free fall during falls. Figure 4.3 shows the typical example of the acceleration and angular velocity signal mimicking the falls. When fall occurs, the acceleration signal is assumed similar when free fall; zero. From parameters selected using random forest analysis in this study; P45 (RMS value of the acceleration signal in medio lateral during walk 1 phase). Referring to Table 3.1, elderly is classify as HFR if the RMS value is lower than 0.14 m/s^2 equivalent to 0.4 m/s^2. Consistent result also obtained by parameter P43; RMS value of acceleration signal in antero posterior direction during walk 1 phase, reported that the elderly will predict as HFR if the RMS value is lower than 0.13 m/s^2 or equivalent to 0.38 m/s^2. In cited paper, considering human posture, the position of the sensor, and the SNR of a low acceleration value, [43] suggested that a prevention acceleration value would be below ± 3 m/s^2. However, lower value were found in this study during walking activity. The sensor location differences between this study and previous researcher might give different result in fall mechanism. Furthermore, the acceleration during fall occurred and acceleration during normal walking should not be the same. In addition, after a preliminary study of angular velocity, [43] added the stipulation that an angular velocity of less than 0.52 rad/s did not indicate a fall. They suggest that a fall occurred when the angular velocity exceeded 0.52 rad/s or equivalent to 29.8 deg/s in pitch direction. Referring to the selected parameters from PCA and random forest analysis, parameter P51; RMS value of angular velocity in pitch direction during walking 1 reported if the RMS value is less than 19.24 deg/s, the elderly will grouped as HFR. This value is equal to 54.41 deg/s peak to peak. The angular velocity value during fall occurred are less than the angular velocity value during walking phase in this. The threshold value used in this study still in the safe zone range in order to prevent the fall risk among elderly before the real falls occurred.

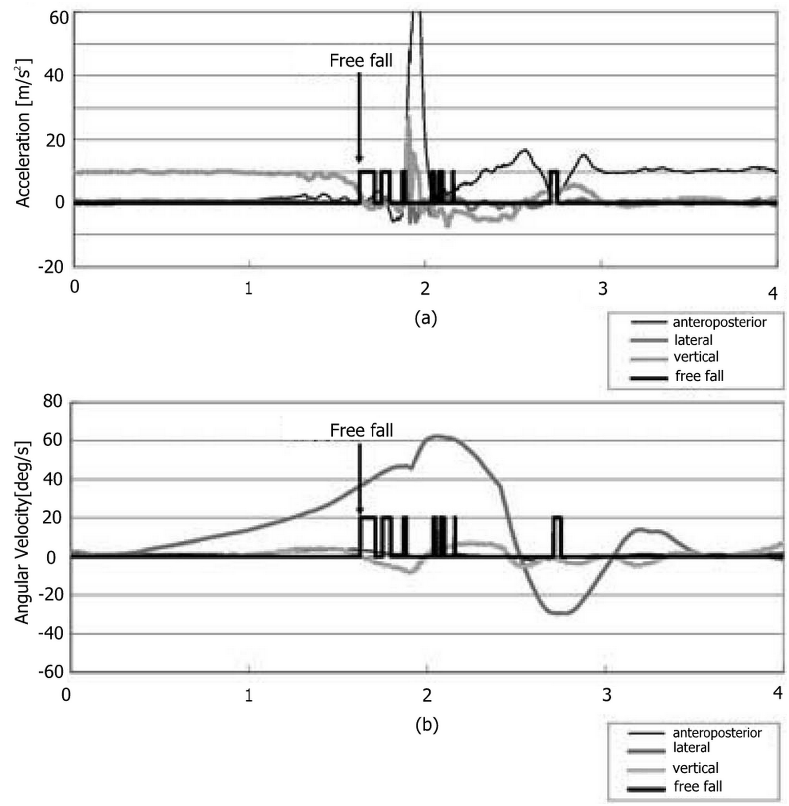


Figure 4.3: Typical example of (a) acceleration and (b)angular velocity waveform while mimicking a forward fall.
(Figure adapted from [43])

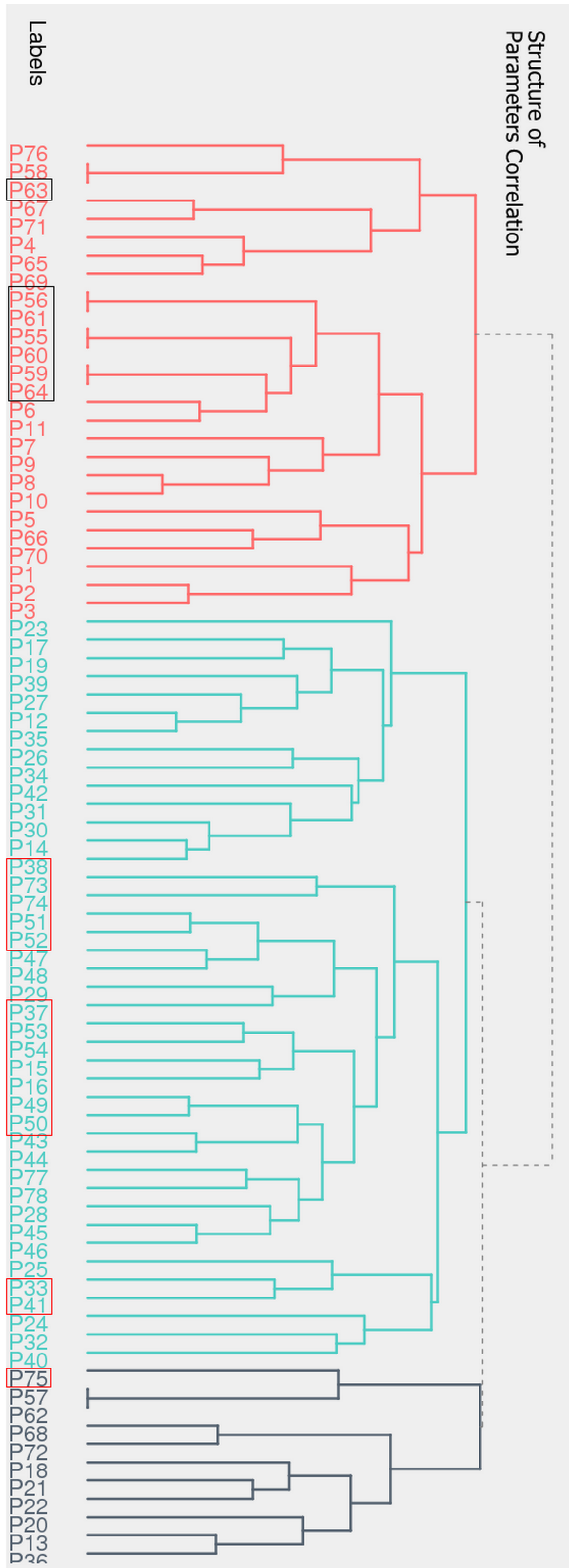


Figure 4.4: Correlation between parameters

The correlation analysis between parameters can be performed on log normalised spot expression levels using dendogram as shown in Figure 4.4. Dendogram showing clusters of spots according to how strongly correlated the spots are. Spots can then be clustered according to how closely correlated the parameters are. Spots with a high correlation value show similar expression profiles while spots which a high negative correlation value show opposing expression profiles.The parameter spots are arranged along the bottom of the dendrogram and referred to as leaf nodes. Comparing Figure 3.12 and above figure, it can be found that the parameters which have positive value in the figure Figure 3.12 are grouped in one branch of tree in above figure; red-boxes. The parameters in same branch have high correlation. This parameters are influence the LFR group. Meanwhile, the parameters that have negative value in in Figure 3.12 is grouped in one branch of tree in above figure highlighted using black boxes. It showed that the parameter in this group have strong correlation and relation between parameters. This inspection indicates that the parameters in branch give more influence to the HFR group.

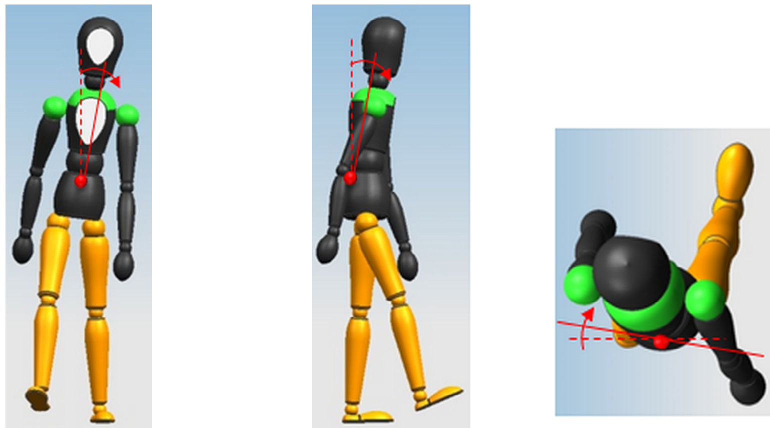
4.6. Parameter Interpretation

From PCA and random forest analysis, several parameters were selected as the most important and most influenced parameter in differentiating the HFR and LFR among elderly. There were 15 parameters were selected using PCA, while 23 parameters were selected using random forest analysis. Among these parameters, 13 parameters were selected by both technique of analysis. The parameters are listed in Table 4.5

Table 4.5: Parameters selected using both PCA and random forest.

	Parameters	Signals	Directions	Phases
P15	Amplitude	Angular Velocity	Yaw	Turn 1
P16	Amplitude	Angular Velocity	Yaw	Turn 2
P33	RMS	Angular Velocity	Roll	Stand-bend
P37	RMS	Angular Velocity	Pitch	Stand-bend
P41	RMS	Angular Velocity	Yaw	Stand-bend
P73	Cadence			Walk 1
P77	Speed			Walk 1
P78	Speed			Walk 2
P49	RMS	Angular Velocity	Pitch	Walk 1
P50	RMS	Angular Velocity	Roll	Walk 2
P51	RMS	Angular Velocity	Pitch	Walk 1
P52	RMS	Angular Velocity	Pitch	Walk 2
P53	RMS	Angular Velocity	Yaw	Walk 1

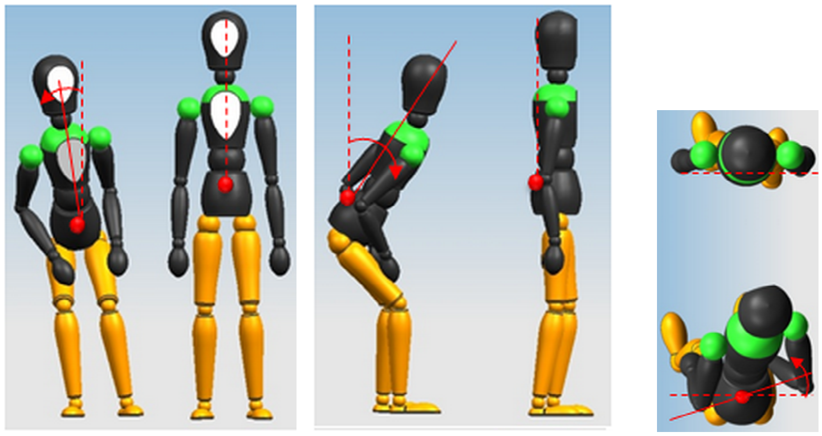
Speed parameters P77 and P78 were selected as two of the important parameter in differentiating the HFR and LFR among elderly. Refering to Table 3.1, as expected HFR subjects have slower speed during walking. The speed correlated with the time linearly as per discussed by previous researcher [1]. Another parameter that was also selected as important parameter in differentiating the HFR and LFR in walking phase is cadence. [8] also found that cadence is a significant parameters in measuring the mobility. The variable cadence have correlation with the speed, therefore the HFR subject have smaller cadence agreed to the smaller value of gait speed. The small value in parameter speed and cadence maybe due to the movement difficulties during gait by HFR elderly and maybe due to the fear of falling which is a monumental obstacle for some and can limit the activities and mobility. This was discussed by [44] that the fearful group had a significantly lower gait speed than did the fearless group.



(a) Roll direction (b) Pitch direction (c) Yaw direction

Figure 4.5: Walking phase movement in roll, pitch and yaw directions

Apart from speed and cadence parameter, RMS value of angular velocity signal in all direction also listed as the influenced parameters in differentiating the HFR and LFR subjects. During the release phase in gait to move forward, the center of pressure will move posteriorly towards the swing limb. For HFR subject, the weight shift slowly accelerate the center of mass towards the stance limb. As a result, the RMS angular velocity in roll direction reffered to the Table 3.1 are small. The hip flexion occured when the subject swing their legs slowly exhibit small RMS value of angular velocity in the pitch direction. During the gait, the trunk subject also rotate slowly to the left and right during the single support in order to move the swing limb forward. The body will move slowly to the left and right resulting a small RMS value of angular velocity signal in yaw direction.



(a) Roll direction (b) Pitch direction (c) Yaw direction

Figure 4.6: Stand-bend phase movement in roll, pitch and yaw directions

Parameters from stand-bend phases were also selected by both analysis as an interesting activity that significant in differentiating the elderly of their falling risk. The parameters of angular velocity in all directions were selected. The asymmetrical motion occurred during the stand bend phase, therefore, all 3 directions; roll pitch and yaw were selected. During the stand-bend activity, subject in HFR slowly tilt to the left and right detected by the roll direction of angular velocity signal. Slowly tilt forward and backward; shown by the angular velocity signal in pitch direction. And slowly rotate as proved by the angular velocity signal in yaw direction. However, the slow motion in all direction exhibit small RMS value of the angular velocity signal.

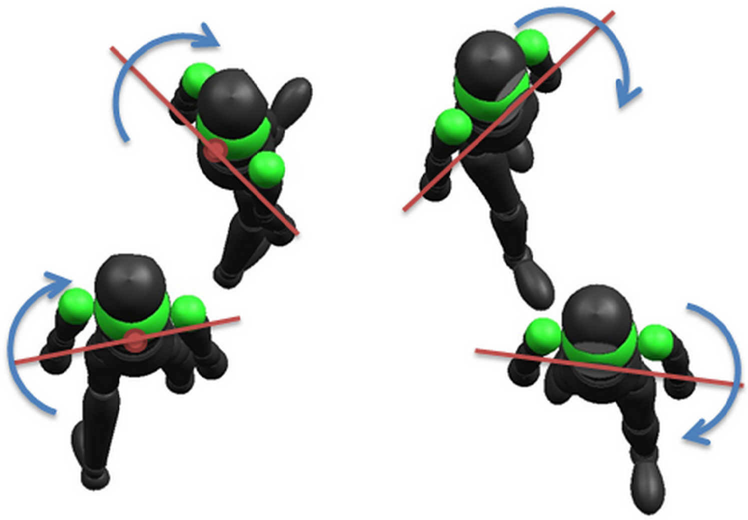


Figure 4.7: Yaw direction during turning phase.

Paramaters P15 and P16; which is the amplitude of the angular velocity signal in yaw direction during turning have the highest ranking in the importance of the parameter selected by both PCA and random forest analysis. During the turning phase, HFR subjects have significantly smaller amplitude of angular velocity compared to the LFR subjects. During the turning activity, the body rotate to the left or right to change the direction as shown in Figure 4.7. During the rotation, movement in roll and pitch direction are very small compared to the yaw direction and do not play an important roll in this action. The same result also were found by the [8]. They found that among the subcomponent in iTUG, gait, turn and turn-to-sit were the most reliable.

4.7. New Proposed Method

From Table 3.5 and Table 3.7, we may summarize that the most important parameters influenced the data is the P16, P75, P15, P77 and P78. The results seem to indicate that the most important parameter found in this research are in turning phase and walking phase. Turning difficulties are common in elderly. The impact from the result, it is thought that a new method simplifying the original method may be ample to be considered in evaluating the fall risk among elderly. The new method proposed as below:

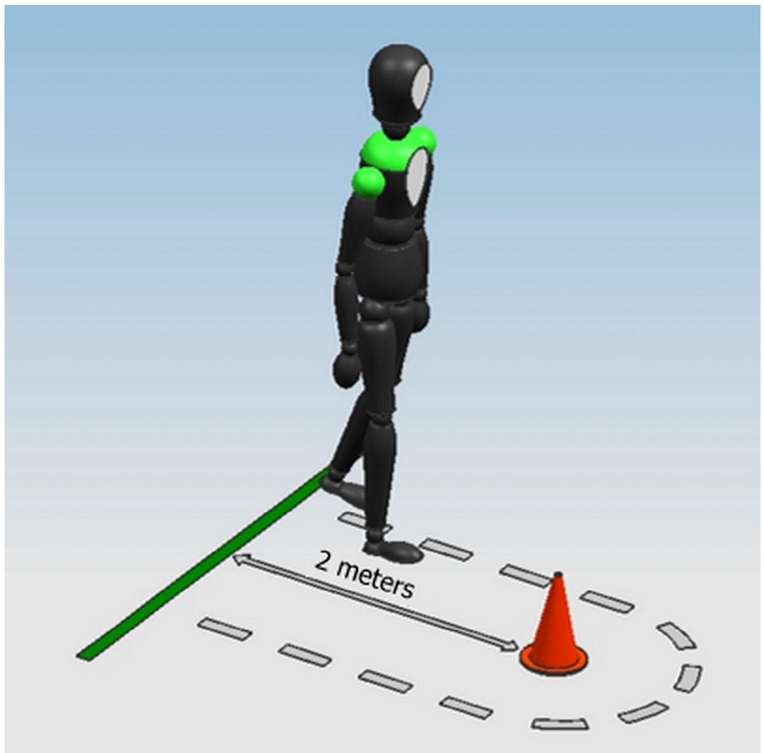


Figure 4.8: New proposed method

Figure 4.8 shows the view of the new proposed method. This method considering the turn phase, instead of the whole phases in the TUG test to screen balance problems and evaluate falling risk. Three steps are required for a steady walking before turning. [45] discussed the average step length by women and men refering to their age. For a steady walking, 3 steps is required. Table 4.6 listed the step length of elderly aged 60 years old and above, and also 70 years old and above for men and women. Referring to the table, the average step length is about 0.65m. If three steps are required, it appears that 1.95 meters required for steady walking. In addition, HFR elderly have smaller step length compared to normal elderly. Therefore, 2 meters of walking phase is enough. By implementing this new propose method, we can handle the experiment using only the tuning phase begins with 2 meters walking in simplifying the experiment in smaller area and in shorter time.

Table 4.6: Step length for men and women aged 60 and 70 and above.

	Age	Step length[m]
Men	Aged above 60	0.65 ± 0.04
	Aged above 70	0.61 ±0.05
Women	Aged above 60	0.55 ± 0.04
	Aged above 70	0.54 ±0.04

The subjects wore the wearable inertial sensors at the waist dorsally and performed the test. The test was consulted by a therapist was as follows:

1. Subject starts to walk for 2 meters from the starting line and reaching the mark post.
2. Subject turns after reaching the marked post.
3. Subject returns to mark line, again over a distance of 1 meters.
4. Subject turns to change facing original direction.

The main phase of this new method is to test the subject ability during turning phase off from the walking phase.

Chapter 5

Conclusion

> Prophet SAW said:"Allah has revealed to me that you must be humble, so that no one oppresses another and boasts over another."
>
> Dawud, Abu

In this study, the use of single wearable inertial sensor for evaluating fall risk in the elderly in different activity phases was proposed. This project also attempt to classify the elderly subject into two groups using multiple parameter at one time in determining the fall risk among elderly in each phase. From the acceleration signal; anteroposterior, mediolateral and vertical directions, and from the angular velocity signal of the roll, pitch and yaw direction, 78 parameters were gathered with 44 have significant different in all phases. Fall risk evaluation using the time duration parameter could not interpret the activity in each phase; hence, using relevant parameters related to appropriate signals and directions could reveal a subjectfs activities in each phase.

Previous study indicates the classification of falling risk using time parameter [1]. Researcher then improved the study by providing some quantitative data and classify the falling using a parameter at one time [6–8]. Analysis by phase could detect not only the fall risk among the elderly, but could also provide extra knowledge for a therapist to understand a subject's performance in different phases. In the first application, we present a method of classification using the k-

NN algorithm to determine the fall risk among elderly. The classification between two groups were done and results of some parameters could classify the group well, however some could not due to parameter selection is insufficient. At one time, we only could classify the the elderly using two selected parameters. The limitation to only two parameters at one time, and the parameters selection difficulty encourage us to use the multivariate analysis.

In the second application, by using PCA and RF, we obtained reduced number of parameters to optimize prediction algorithm implemented on the sensor. We applied the significant 44 parameters with PCA, and ranked the most important and the least important parameters. As a result, some unimportant parameters were removed; which least influenced the classification. The classification performance can still be improved using the random forest analysis. This analysis is based on decision tree could classify the HFR and LFR with higher recognition rate. However, the due to false negative and positive negative result in both analysis, the PCA and RF analysis resulting almost the same performance. In regard to this result, we could classify the elderly to HFR and LFR with lower error rate using LDA.

Despite of reducing the unimportant parameters and selecting the most influenced parameter, PCA could visualize and mapping all parameters with the all subjects at one time. This improve the way how therapist could read and reveal the subjectfs movement activity during therapy session.

Using the wireless inertial sensor, further prediction and classification of fall risk among elderly are enable from obtained parameters, and the extracted information could interpret subjectfs condition well beyond simply the time taken to perform the test. In general, our study improve the classification using multi parameters in phases, providing movement information to the therapist by harnessing the quantitative information from the parameters. We believe that the use of multi parameters in distinct phases could enhance the classification method, and thus harnessing the quantitative information provided the therapist with more valuable information in improving the rehabilitation area.

Acknowledgements

Alhamdulillah, praise to the Almighty, with His grace I can at least breath a sigh of relief that the thesis is now completed. In preparing this project, I was in contact with many people, researchers, and academicians. First of all, I wish to express my sincere appreciation to my supervisor, Professor Shigehiko Kanaya and Kotaro Minato, who gave me the opportunity to study in their laboratory. I greatly appreciate all their assistance and support during my studies in the laboratory. Their warmth and kind attention have made me feel very welcome. Also my deep appreciation addressed to Professor Toshiyo Tamura from Osaka Electro-communication University who supervised me from the very first of my project during in Chiba University and continuously assisted and encouraged me during my study in Naist.

I would like to thank my thesis committee, Professor Shigehiko Kanaya, Professor Tsukasa Ogasawara, Professor Toshiyo Tamura and Associate Professor Tadao Sugiura for their valuable comments and supervision of my work. Their valuable encouragement, guidance, critics improved the achievement of this dissertation.

I wish to express my sincere appreciation to Associate Professor Md.Altaf-Ul-Amin, Assistant Professor Tetsuo Sato,, Assistant Professor Naoaki Ono Assistant Professor Takumu Hittori and for their valuable support, comments and hospitality during my stay in the lab. Without their continued support and courage, this project report would not have been the same as presented here.

Thank you to Dr. Masaki Sekine and Dr. Noriko Tanaka from Osaka Electro-communication University for their supervision and comments for the improvement of the research in the application of wearable inertial sensors and experiment.

Thank you to all members and staff of Biomedical Imaging and Informatics Laboratory, in NAIST, and all members and staff in Medical System Laboratory in Chiba University for their friendly support and hospitality. Their cheerfulness and friendship during my stay in Japan and during my work in the laboratory keep the warm horizon among us.

I am also indebted to Universiti Teknologi Malaysia (UTM) for their financial support during my doctoral course in Japan. The scholarship has offered me a wide and useful knowledge and new experience.

Last but not least, my appreciation also extends to my beloved husband, Fairuz and my lovely son, Izzul Iman whose provided assistance at various occasions. Their meaningful encouragement, understanding and prays boost me to achieve my doctoral degree. Finally, I am also very grateful to all my family members anf friends for their continuous support and prays.

Publication List

Journal

1. Nor Aini Zakaria, Yutaka Kuwae, Toshiyo Tamura, Kotaro Minato, Shigehiko Kanaya, Quantitative Analysis of Fall Risk Using TUG Test, *Journal of Computer Methods in Biomechanics and Biomedical Engineering*, (In press)(in chapter 2 and 3).

International Conferences

1. Zakaria Nor Aini, Numata Takayuki, Tamura Toshiyo, Minato Kotaro. Quantitative analysis of falls risk using TUG(TIME UP and GO) test. In *Abstract of World Congress on Medical Physics and Biomedical Engineering (WC2012)*, Oral Presentation. Beijing, May 2012.(in chapter 2 and 3).

2. Zakaria Nor Aini, Kibinge Nelson Kipchirchir, Kanaya Shigehiko, and Tamura Toshiyo. Fall risk classification with multivariate analysis. *10th International Conference on Ubiquitous Healthcare 2013*, Oral Presentation. Yokohama-Japan. September 2013.(in chapter 2 and 3).

Domestic Conferences

1. Zakaria Nor Aini, Yutaka Kuwae, Tamura Toshiyo, Minato Kotaro. Classification of falling risk subject by the wearable inertial sensor. *Abstract of Japan Biological and Medical Engineering Symposium 2012 (JBMES2012)*, Poster Presentation. Osaka-Japan. September 2012.(in chapter 2 and 3).

References

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

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

[3] Cris Zampieri, Arash Salarian, Patricia Carlson-Kuhta, Kamiar Aminian, John G Nutt, and Fay B Horak. The instrumented timed up and go test: potential outcome measure for disease modifying therapies in parkinson's disease. *Journal of Neurology, Neurosurgery & Psychiatry*, 81(2):171–176, 2010.

[4] Gyrd Thrane, Ragnar M Joakimsen, and Eline Thornquist. The association between timed up and go test and history of falls: The tromso study. *BMC Geriatrics*, 7(1):1, 2007.

[5] A Shumway-Cook, S Brauer, and M Woollacott. Predicting the probability for falls in community-dwelling older adults using the timed up and go test. *Physical Therapy*, 80(9):896–903, 2000.

[6] Y. Higashi, K. Yamakoshi, T. Fujimoto, Masaki Sekine, and T. Tamura. Quantitative evaluation of movement using the timed up-and-go test. *Engineering in Medicine and Biology Magazine, IEEE*, 27(4):38–46, 2008.

[7] Barry R Greene, Alan O'Donovan, Roman Romero-Ortuno, Lisa Cogan, Cliodhna Ni Scanaill, and Rose A Kenny. Quantitative falls risk assessment using the timed up and go test. *IEEE Transactions on Biomedical Engineering*, 57(12):2918–2926, 2010.

[8] Arash Salarian, Fay B Horak, Cris Zampieri, Patricia Carlson-Kuhta, John G Nutt, and Kamiar Aminian. itug, a sensitive and reliable measure of mobility. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 18(3):303–310, 2010.

[9] M J Mathie, B G Celler, N H Lovell, and A C F Coster. Classification of basic daily movements using a triaxial accelerometer. *Medical & Biological Engineering & Computing*, 42(5):679–687, 2004.

[10] M C Hornbrook, V J Stevens, D J Wingfield, J F Hollis, M R Greenlick, and M G Ory. Preventing falls among community-dwelling older persons: results from a randomized trial. *The Gerontologist*, 34(1):16–23, 1994.

[11] J M Hausdorff, D A Rios, and H K Edelberg. Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of Physical Medicine and Rehabilitation*, 82(8):1050–1056, 2001.

[12] Jaap Swanenburg, Eling D De Bruin, Daniel Uebelhart, and Theo Mulder. Falls prediction in elderly people: a 1-year prospective study. *Gait & Posture*, 31(3):317–321, 2010.

[13] James B Lee, Rebecca B Mellifont, and Brendan J Burkett. The use of a single inertial sensor to identify stride, step, and stance durations of running gait. *Journal of Science and Medicine in Sport*, 13(2):270–273, 2010.

[14] Ruth E Mayagoitia, Anand V Nene, and Peter H Veltink. Accelerometer and rate gyroscope measurement of kinematics: an inexpensive alternative to optical motion analysis systems. *Journal of Biomechanics*, 35(4):537–542, 2002.

[15] J C Wall, C Bell, S Campbell, and J Davis. The timed get-up-and-go test revisited: measurement of the component tasks. *Journal of Rehabilitation Research And Development*, 37(1):109–113, 2000.

[16] Martin Hofheinz and Claudia Schusterschitz. Dual task interference in estimating the risk of falls and measuring change: a comparative, psychometric study of four measurements. *Clinical Rehabilitation*, 24(9):831–842, 2010.

[17] Maria Gine-Garriga, Miriam Guerra, Marc Mari-Dell Olmo, Carme Martin, and Viswanath B Unnithan. Sensitivity of a modified version of the ?gtimed get up and go?h test to predict fall risk in the elderly: a pilot study. *Archives of Gerontology and Geriatrics*, 49(1):e60–e66, 2009.

[18] Denise McGrath, Barry R Greene, Emer P Doheny, David J McKeown, Giuseppe De Vito, and Brian Caulfield. Reliability of quantitative tug measures of mobility for use in falls risk assessment.

[19] Weijun Tao, Tao Liu, Rencheng Zheng, and Hutian Feng. Gait analysis using wearable sensors. *Sensors (Peterboroug)*, 12(2):2255–2283, 2012.

[20] Che-Chang Yang and Yeh-Liang Hsu. A review of accelerometry-based wearable motion detectors for physical activity monitoring. *Sensors (Peterboroug)*, 10(8):7772–7788, 2010.

[21] Bijan Najafi, Kamiar Aminian, Fran?ois Loew, Yves Blanc, Philippe A Robert, and Senior Member. Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly. *IEEE Transactions on Biomedical Engineering*, 49(8):843–851, 2002.

[22] Hiroaki Miyoshi, Takayuki Numata, Yutaka Kuwae, Masaki Sekine, Miwa Tsuji, Ichiro Okabe, Keita Hara, Toshiro Fujimoto, and Toshiyo Tamura. Evaluation of lower limb motor function using wireless motion sensors:a comparison of normal elderly subjects and those requiring support level 1. *Electronics and Communications in Japan*, 95(12):37–45, 2012.

[23] Che-Chang Yang, Yeh-Liang Hsu, Kao-Shang Shih, and Jun-Ming Lu. Real-time gait cycle parameter recognition using a wearable accelerometry system. *Sensors Basel Switzerland*, 11(8):7314–26, 2011.

[24] F Gemperle, C Kasabach, J Stivoric, M Bauer, and R Martin. Design for wearability. *Digest of Papers Second International Symposium on Wearable Computers Cat No98EX215*, pages 116–122, 1998.

[25] Che-Chang Yang and Yeh-Liang Hsu. Development of a wearable motion detector for telemonitoring and real-time identification of physical activity. *Telemedicine Journal and EHealth*, 15(1):62–72, 2009.

[26] M Sekine, T Tamura, T Togawa, and Y Fukui. Classification of waist-acceleration signals in a continuous walking record. *Medical Engineering and Physics*, 22(4):285–291, 2000.

[27] Dean M Karantonis, Michael R Narayanan, Merryn Mathie, Nigel H Lovell, and Branko G Celler. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. *IEEE transactions on information technology in biomedicine*, 10(1):156–167, 2006.

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

[29] Yuancheng Jian, Da Winter, Mg Ishac, and L Gilchrist. Trajectory of the body cog and cop during initiation and termination of gait. *Gait Posture*, 1(1):9–22, 1993.

[30] Miroslav Janura, Petra Gaul Aláčová, Marcela Míková, and Petra Hanáková. Evaluation of the stability of sit-to-stand. *Department of Biomechanics and Engineering Cybernetics, Faculty of Physical Culture, Palacky University, Olomouc, Czech Republic*, 2003.

[31] M Schenkman, R A Berger, P O Riley, R W Mann, and W A Hodge. Whole-body movements during rising to standing from sitting. *Physical Therapy*, 70(10):638–648; discussion 648–651, 1990.

[32] A Weiss, T Herman, M Plotnik, M Brozgol, N Giladi, and J M Hausdorff. An instrumented timed up and go: the added value of an accelerometer for identifying fall risk in idiopathic fallers. *Physiological Measurement*, 32(12):2003–18, 2011.

[33] Emer P Doheny, Chie Wei Fan, Timothy Foran, Barry R Greene, Clodagh Cunningham, and Rose Anne Kenny. An instrumented sit-to-stand test used to examine differences between older fallers and non-fallers.

[34] Milica D Djuric-Jovicic, Nenad S Jovicic, and Dejan B Popovic. Kinematics of gait: New method for angle estimation based on accelerometers. *Sensors (Peterboroug)*, 11(11):10571–85, 2011.

[35] Wiebren Zijlstra and Kamiar Aminian. Mobility assessment in older people: new possibilities and challenges. *European Journal of Ageing*, 4(1):3–12, 2007.

[36] Marius Henriksen, H Lund, R Moe-Nilssen, H Bliddal, and B Danneskiod-Samsoe. Test-retest reliability of trunk accelerometric gait analysis. *Gait & Posture*, 19(3):288–297, 2004.

[37] M Morris, R Iansek, T Matyas, and J Summers. Abnormalities in the stride length-cadence relation in parkinsonian gait. *Movement disorders official journal of the Movement Disorder Society*, 13(1):61–69, 1998.

[38] Yea-Ru Yang, Ya-Yun Lee, Shih-Jung Cheng, Pei-Yi Lin, and Ray-Yau Wang. Relationships between gait and dynamic balance in early parkinson's disease. *Gait & Posture*, 27(4):611–615, 2008.

[39] Jiawei Han and Micheline Kamber. *Data Mining: Concepts and Techniques*. Morgan Kaufmann, 2000.

[40] Thomas M. Mitchell. *Machine Learning*. McGraw-Hill, Inc., New York, NY, USA, 1 edition, 1997.

[41] Leo Breiman. Random forests. *Machine Learning*, 45(1):5–32, 2001.

[42] Robin Genuer, Jean-Michel Poggi, and Christine Tuleau-Malot. Variable selection using random forests. *Pattern Recognition Letters*, 31(14):2225–2236, 2010.

[43] Toshiyo Tamura, Takumi Yoshimura, Masaki Sekine, Mitsuo Uchida, and Osamu Tanaka. A wearable airbag to prevent fall injuries. *IEEE transactions on information technology in biomedicine*, 13(6):910–914, 2009.

[44] Melissa E Chamberlin, Brandy D Fulwider, Sheryl L Sanders, and John M Medeiros. Does fear of falling influence spatial and temporal gait parameters in elderly persons beyond changes associated with normal aging? *The journals of gerontology Series A Biological sciences and medical sciences*, 60(9):1163–1167, 2005.

[45] T Oberg, A Karsznia, and K Oberg. Basic gait parameters: reference data for normal subjects, 10-79 years of age. *Journal Of Rehabilitation Research And Development*, 30(2):210–223, 1993.