SEMI-AUTOMATIC FALLS RISK ESTIMATION OF ELDERLY ADULTS USING SINGLE WRIST WORN ACCELEROMETER

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ABSTRACT

The population of the oldest old (aged 85 years and over) is growing. It is estimated that 30% of the adults over the age of 65 years experience falls at least once a year. This figure rises to 50% per annum for adults over 80 years living either at home or in care home. Currently older people are the fastest growing segment of the population. In the UK alone, the proportion of people aged 85 years old has increased from 2% to 4% in the past six decades. This marked increase in growth of population aged over 85 years is expected to have substantial impact on overall falls rate and pose serious issues to meet care needs for social and health care departments. In the light of such negative consequences for the faller and the associated costs to society, simple and quantitative techniques for falls risk screening can contribute significantly.

This study describes a semi-automated technique to estimate falls risk of community dwelling elderly adults (aged 85 and over). This study presents the detailed analysis of tri-axial accelerometer movement data recorded from the right wrist of individuals undertaking the Timed Up and Go (TUG) test. The semi-automated assessment is evaluated here on 394 subjects' data collected in their home environment. The study compares logistic regression models developed using accelerometer derived features against the traditional TUG measure 'time taken to complete the test'. Gender based models were built separately across two groups of participants- with and without walking aid. The accelerometer derived feature model yielded a mean sensitivity of 63.95%, specificity of 63.51% and accuracy of 66.24% based on leave one-out cross validation compared to manually timed TUG (mean sensitivity of 52.64%, specificity of 45.41% and accuracy of 55.22%). Results show that accelerometer derived models offer improvement over traditional falls assessment. This automated method enables identification of older people at risk of falls residing both at home and in care homes and to monitor intervention effectiveness of falls management.

To My Family

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ABBREVIATIONS

AUC	Area Under the Curve
BBS	Berg Balance Scale
DGI	Dynamic Gait Index
LDA	Linear Discriminant Analysis
LOOCV	Leave One Out Cross Validation
MEMS	Micro Electro Mechanical systems
NOS	Number of Frequency Switches
PD	Parkinson's Disease
ROC	Receiving Operating Characteristics
SD	Standard Deviation
SMPS	Sum of Magnitude of Power Spectrum
SVM	Signal Vector Magnitude
TUG	Timed Up and Go Test
WoA	With Out Aid
WA	With Aid

PUBLICATIONS

1. *SankarPandi, S.K.; Dlay, S.; Wai Lok Woo; Catt, M., "Can Accelerometer Placed at Wrist Enhance Utility of Timed Up and Go test?", IEEE Trans. on Neural Systems and Rehabilitation Engineering, 2014, under Review.*

2. *SankarPandi, S.K.; Dlay, S.; Wai Lok Woo; Catt, M., "Predicting disability levels of community dwelling older individuals using single wrist mounted accelerometer," Biomedical and Health Informatics (BHI), 2014 IEEE-EMBS International Conference on , vol., no., pp.720,723, 1-4 June 2014.*

Chapter 1

1 Introduction

In many developed countries, falls are emerging as one of the serious health related issues among aging populations. One in three of population aged over 60 years' experience falls at least once a year. Of this population 50% of the fallers fall repeatedly, 10% of falls result in serious injury and around 20% require medical attention.

In the UK alone, £203 million ($331 million) was spent annually to treat fatal and non-fatal falls for people aged 80 and over in 2010 imposing a substantial financial burden to the health care services [1]. Apart from financial burden falls in elders causes additional psychological disturbances. Moreover, elders develop a fear of fall after the post fall event, which hinder their regular activities which further increases the risk of fall to about 46% and increases the length of rehabilitation and thus cost [2].

Occurrence of falls increases with age. Multiple studies have shown that older people (over 65 years) are the fastest growing segment of the population and this trend is expected to continue [3]. In the UK alone, the proportion of people aged 85 years old has increased from 2% to 4% in the past six decades [4]. This marked increase in growth of population aged over 85 years is expected to have substantial impact on overall falls rate and pose serious issues to meet care needs for social and health care departments. Therefore, in this present scenario given the marked increase proportion of elderly population, falls identification and prevention becomes vital.

Advent of Micro Electro Mechanical Systems (MEMS) technology has driven the development of wearable sensors/ambulatory monitors. These wearable sensors allow recording body movements during the daily activities of living and detect falls. In the past, many falls detection systems [5-7] were implemented using wearable sensors which detects falls as occurs. Getting assistance quickly after occurrence of falls increases the chances of living and hence many fall detection systems were developed to generate alarm for help. Although, detection of falls saves life by significant percentage, the injuries and after effects of falls are high in number. Moreover, the falls detection system only detects falls. Injury, cost for treatments and psychological effects are still pertinent even after falls detection. Therefore a compelling necessity has evolved preventing falls than detecting it. A study by Tinetti *et al.* [8] showed that falls can be prevented with effective falls risk assessment strategies which has significant benefits of reducing injuries, hospitalizations, nursing home admissions, functional decline and reduces the money spend to treatments of falls.

In 2003, lord *et al.* [9] described a conceptual model for falls assessment and identified that the main factor for falls is postural instability. The major contributors for postural stability are vision, reaction time, muscle force, vestibular function, and peripheral sensation [9]. Hindrances in any of these factors contribute to instability leading to falls. As a result, assessments of these factors permit estimating degree of fall risk. Similarly, British and American geriatric societies proposed a guideline for falls assessment in order to identify and offer interventions preventing falls [10]. The simplified flow chart of proposed guideline is shown in the Figure 1.1. Health care provider offers the falls screening questionnaire to an elderly adult. Then balance and gait is assessed, if any abnormality is detected then multi factorial assessment is carried out. Based on its outcomes of multi factorial assessment interventions are offered. Once interventions are offered elderly adults are reassessed periodically and procedure above is carried out to offer interventions thereby preventing falls.

It can be seen from the flowchart that gait and balance determine postural stability of an elderly and identified as the major factor for assessing falls. Therefore, gait and balance has to be assessed to evaluate the falls risk and prevent them. Traditionally, gait and balance of an elderly are assessed using clinical tests such as Berg Balance test, Tinetti test, Dynamic Gait Index. In particular, one or more clinical tests are administered to an elderly participant and performance of the participant is evaluated by the examiner/trained clinical staff using clinical scales. As the assessments are based on clinical rating scales the results suffer from drawbacks such as examiner bias, not accurate and time consuming.

Wearable sensors allow quantification of body movements during the clinical tests and allow overcoming the issues of direct evaluation by an examiner. More interestingly, wearable sensors show potential for automating the whole process of gait and balance evaluation and thereby identification of falls. Automated and quantified assessment of falls permits simple, quick and accurate fallers identification at early stages of balance and gait deficits. Early identification of risk factors will allow offering interventions to prevent falls. In addition, quantified assessment allows evaluating falls in elderly home living environment, this might broaden the scope of falls assessment beyond the clinical setting and contribute to falls risk screening significantly.

The overall aim of the study is to develop and implement techniques to automatically assess balance and gait using wearable sensors that enable to predict falls of elderly adults in home living environment.

1.1. Thesis aims and Objectives

The primary aim of the research is to investigate the feasibility of using single wrist mounted accelerometer to predict fallers automatically in a community dwelling. Aims and objectives of the research are outlined as follows:

1.1.1. Aims

The study is undertaken to study the following primary hypothesis:

- Is it feasible to use single wrist mounted accelerometer to predict fallers in the community dwelling?
- Does accelerometer have any added value and improve falls prediction in comparison with traditional falls prediction methods?
- Is it possible to automate the whole process of falls estimation and can it be used in community dwelling environment?
- Can disability levels be predicted using accelerometer and does it have any added value compared to traditional measurement?

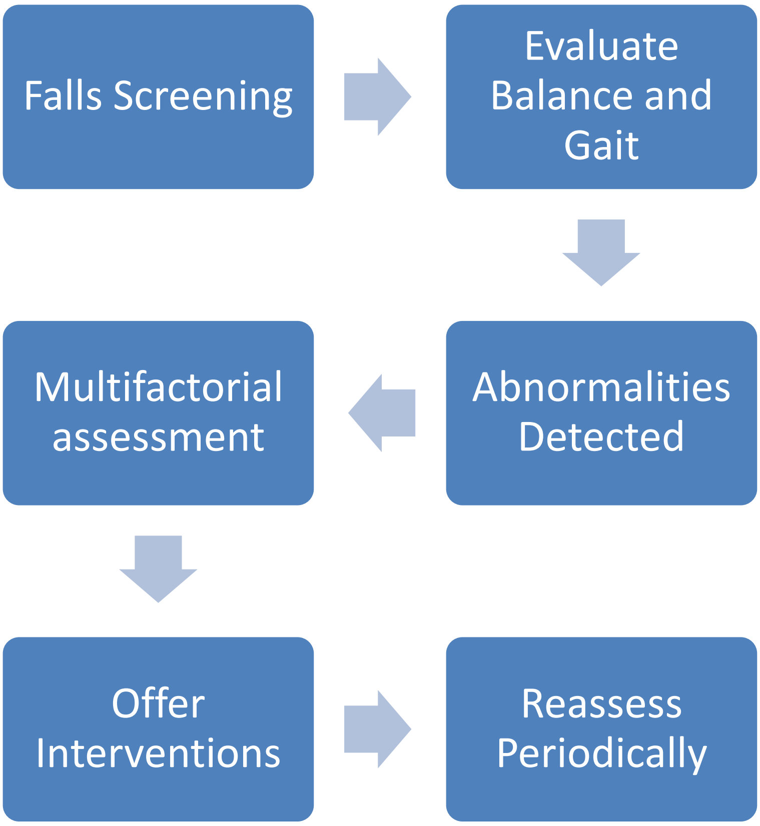

Figure 1.1 Simplified flowchart of falls assessment described by British and American geriatrics society [10].

1.1.2. Objectives

The study has the following primary objectives:

- Develop and implement clear, simple and acceptable protocol to automate falls prediction that enables application in normal living environment.

- Extract clinically sensitive features from the signals of accelerometer that may associate with falls and health status which enables identifying falls in early.
- Develop and implement classifier independent robust feature selection methodologies to select and combine extracted features that have ability to predict fallers.
- To gain insight into the importance of features extracted and study its effectiveness.

1.2. Thesis Contributions

The novel contributions of this research study are summarised as below:

- A novel protocol and algorithm was implemented to identify the actual signals of interest from the whole accelerometer recording. The algorithm developed delineates signals automatically with mere user tapping the sensor before and after the test.
- The implemented algorithm to identify signals of interest was compared with the true measurement and error was found to be less than 0.1s.
- A new feature known as ‘Number of Frequency Switches (NOS)’ was extracted and its ability to discriminate fallers from non-fallers was shown. Moreover, this feature’s ability to classify disability levels is also presented.
- A generalised feature selection algorithm which is independent of classifiers was developed.
- Simple Logistic Regression classifier to identify falls was developed using the combination of selected features. The developed model showed an

improvement of accuracy of ~10% over the model developed using traditional measure.

- The extracted features have shown its ability to discriminate disability level of community dwelling adults. The accelerometer based model outperforms the model developed using traditional measure classifying disability levels. On a whole, the developed system has an added value and can identity fallers and also disability level of an individual living in home environment or in clinical environment with minimum user aid.

1.3. Outline of the thesis

The basic motivation for this study, aims and objectives are provided in the Chapter 1, the structure of the thesis is as follows:

Chapter 2 introduces falls and the risk factors that manifests falls. Subsequently, techniques used to asses fall are introduced. Followed by, introduction to ambulatory monitors and its benefits of assessing falls over traditional methods. Later, it reviews literatures which utilised ambulatory monitors for the assessment of falls risk. Finally, it provides background information and theory of feature selection and classification system used in this study.

Chapter 3, Compares the methods of studying falls and approaches to estimate falls. The chapter presents the requirements of ambulatory monitor and presents the wearable accelerometer used in the study. Finally, it presents the signals obtained from the accelerometer and the methodology used for estimating the components of the accelerometer signals.

Chapter 4, presents the advantages of automatic falls estimation. It details the protocol and algorithm developed to semi-automatically estimate falls. Later, the chapter presents the methodology of features extracted and its usefulness. Finally, it describes the methodology of robust feature selection implemented.

Chapter 5 presents the results and discussion of the study. The first section of the study presents the performance of the signal segmentation algorithm. Subsequently, the performance metrics of models developed for falls estimation using the features selected and combined are presented. Finally, it studies the ability of extracted features to estimate the disability levels in the community dwelling and presents the performance metrics of the models developed.

Chapter 6 presents the conclusion and future work of the study.

Chapter 2

2. Theory and Background

This chapter depicts the motivation and background information of the study undertaken. The chapter is divided into three main sections. The first section introduces falls, falls risk factors and techniques that are widely used to assess falls risk. The second section of the chapter, describes benefits of ambulatory monitors over the traditional methods assessing falls risk. It then details the background information, principles of ambulatory monitor-accelerometer used in the study. Subsequently, it reviews the literatures on assessment of falls risk using ambulatory monitors. The third section of the chapter describes theory and background of components of classification system that are utilised in this work.

2.1. Falls

In many developed countries, falls are emerging as one of the serious health related issues among aging populations. Falls are the biggest risk for the elderly population, particularly for the community-dwelling individuals, leading to loss of functional independence. One in three of population aged over 60 years' experience falls at least once a year. Of this population, 50% of the fallers fall repeatedly, 10% of falls result in serious injury and around 20% require medical attention [11]. Incidence of falls increases with age and falls related admission in hospitals increases exponentially after the age of 60 years [12]. Figure 2.1 shows the fatal falls rate by age in USA, it can be clearly seen that falls rate increases with age and particularly after 75 years of age falls rate is remarkably higher.

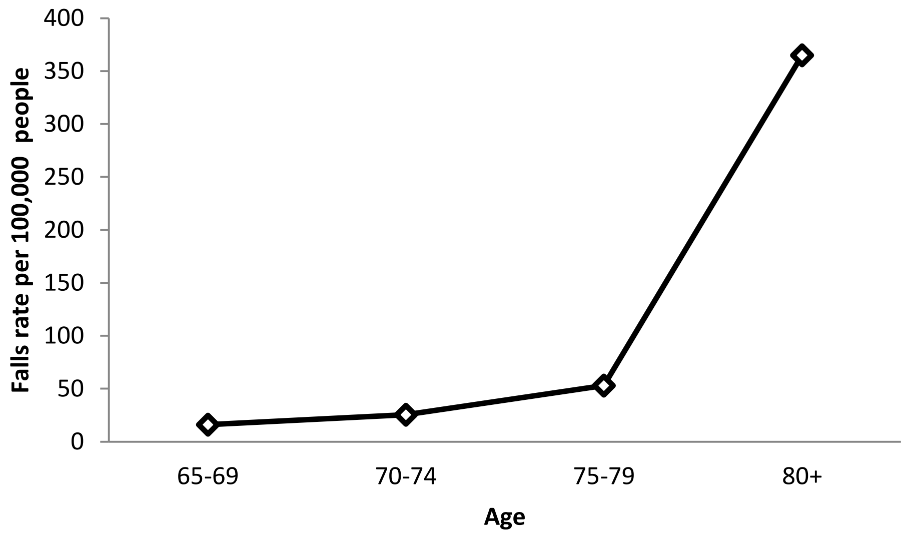

Figure 2.1 Fatal falls rate by age in USA

Falls causes many injuries of those injuries hip fracture is the one of the injuries which generally leads to serious health adversities [13]. Most of the hip fractures lead to death and in case of survival, elderly adults do not recover complete mobility. Apart from hip fractures, falls causes multitude of problems such as head injuries, loss of independence, institutionalisation and admissions to hospitals. Half of the individuals who fall are unable to get up after the fall without assistance, it was reported in the study by Tinetti *et al.*[14] that out of 313 fallers, 47% (148) were unable to get up after fall. Although, some of the falls are non-injurious, lying down after a fall for a long time without being able to get up have serious consequences like, fear of falling, muscle damage, dehydration and hypothermia. These consequences result in hindrance to perform activities of daily living (ADL) which reduces quality of health and well-being further increasing the falls risk.

Falls reduces the quality of life to individuals and also cause enormous cost to the government and health care organisations, therefore identifying fallers earlier in time and preventing falls is imperative. Past literatures on elderly falls show evidences of falls identification and prevention. Although, falls identification systems save life the after effect of falls are still persistent and hence falls prevention is superior to falls identification. To prevent falls, risk factors associated with falls have to be identified at an early stage and timely and targeted interventions have to be provided.

2.1 Falls Risk Factors

Falls are caused by multiple risk factors. The risk factors of falls can be broadly classified into Extrinsic and Intrinsic factors. The extrinsic factors are environmental hazards (poor lighting, slippery floors), lack of safety equipment's in bathrooms and inappropriate walking aids, footwear and clothing [15]. Intrinsic factors are weakness in muscular strength, decline in stability, balance and vestibular function and it is estimated that over 85% of falls are due to intrinsic factors [14]. It is reported in [16] that, multiple disabilities such as limited mobility, poor vision etc. congregate together and cause falls. The underlying causes for falls are compound in nature and are difficult to identify appropriately, consequently different literatures identifies different falls risk factors.

Poor vision is shown to be significant and independent risk factor of falls in multiple studies [17-19]. Factors such as low visual acuity and depth perception are shown to be important measures of vision that relate to falls risk.

Another important falls risk factor is the muscle strength. Muscle strength is one of the factors that define one's ability to maintain balance. There are number of studies which show that the lower limb strength as a strong single independent predictor of falls. In addition to poor vision and muscle strength, ailments such as Alzheimer's and Parkinson's disease are also found to cause falls [20].

Medications taken for the diseases and disabilities have also shown to be significant risk factor of falls. It has been reported that medications like benzodiazepines, anti-depressants and medications that are associated with central nervous systems have connection with increased falls risk [21]. Other factors which have shown association with falls are poor balance and stability, grip strength, slow walking speed, inactivity, poor vision, anxiety, peripheral neuropathy and dependence in performing ADL [14, 22-24]. Figure 2.2 shows the factors that cause falls and effects of falls.

Identification of risk factors of falls help in offering interventions. Interventions help reducing falls. Literatures have shown to have offered interventions considering both single risk factor and multiple risk factors of falls. Although, single factor interventions have its benefits, multi factorial interventions is preferred over as it is more successful in prevention of falls. Studies have shown that multi factorial interventions have led to 25% of less falls [25], 26% less hospitalisations, reduction in time of stay at hospitals [26] and significant reduction in falls rate [27, 28].

In a summary, identification of risk factors is the vital aspect to provide timely and target specific interventions. Effective timely interventions help reducing falls and improve the quality of life of elderly population at risk.

2.2. Techniques for Assessing Falls Risk

Falls risk assessment methods allow assessor to evaluate participants falls risk through assessing their performance. The methods varies widely requiring participants to fill the simple questionnaires to the complex multi factorial assessments which aims to assess the falls risk factors described earlier in section 2.2. Some of the assessment requires participant to perform only a single task and others require performing multiple tasks. Depending upon the number and nature of tasks, assessment methods have been applied in variety of environments from community dwelling natural environment to the hospital settings.

The three most widely used falls risk assessment methods applied on community dwelling individuals are, Berg Balance Scale (BBS) [29, 30], Dynamic Gait Index (DGI) [31] and Timed Up and Go (TUG) test [32]. These tests focus upon the mobility and balance of the participant each with different focus.

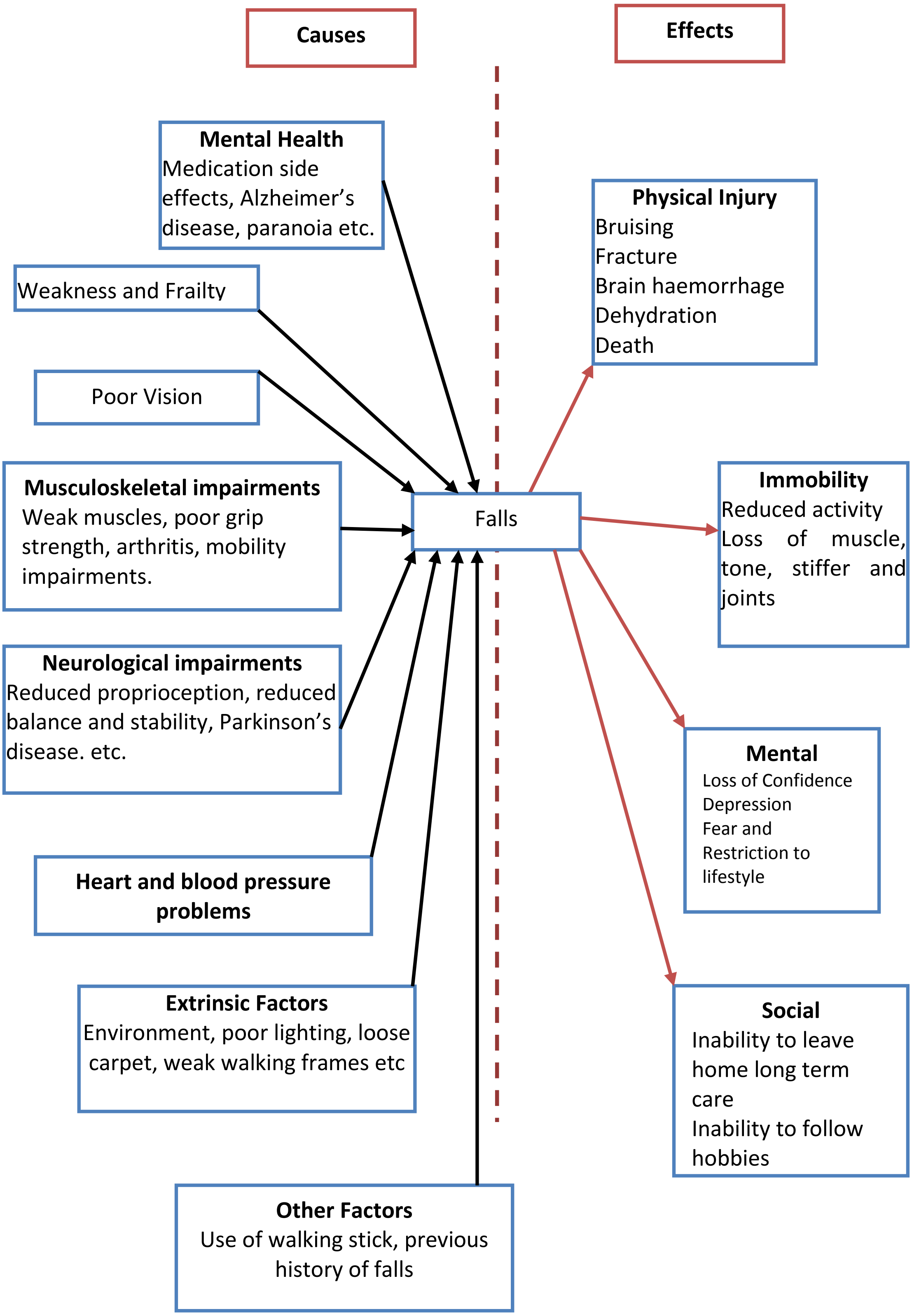

Figure 2.2: Risk factors and effects of falls. Modified and adapted from [33].

2.2.1. Performance Metrics

In the literatures of falls identification the performance metrics that are widely used are presented in this section. The three widely used performance metrics are sensitivity, specificity and accuracy. Sensitivity is defined as the percentage of fallers correctly identified as fallers; it is also called as true positive rate. Specificity is defined as the percentage of non-fallers correctly identified as non-fallers, true negative rate. Accuracy is defined as overall correct percentage of the classifier under test.

2.2.2. Berg Balance Scale (BBS)

Berg Balance Scale is valid [29] and widely used test for assessing balance and stability [34]. BBS consists of 14 balance related activities and usually undertaken under the supervision of the assessor or practitioner. Each of the activity is rated by the assessor in the scale ranging from 0 to 4, where 0 indicating poor performance, summing up to the total score of 56. The 14 tasks include : sitting to standing, standing to sitting, standing unsupported, sitting unsupported, standing with eyes closed, standing with feet together, turning to look behind, turning 360^0, placing alternate foot on stool, standing on one foot on front, standing with one foot on front, transfers, reaching forward with outstretched arm and retrieving object from floor.

BBS has shown to have excellent inter and intra rater reliability and proven as a valid screening tool to identify individuals at falls risk [35]. Different literatures show different BBS cut off scores for identifying elderly adult at risk.

The original recommended cut off by Berg *et al.* [29] was 45, which differentiates healthy participants from those who require care or further examination. Ability of BBS is shown to vary in different studies, Bogle *et al.* [36] supporting the original discriminative score of 45, reported specificity over 90% and sensitivity of 53% identifying fallers from non-fallers. Shumway *et al*.[37] undertook a study to predict fallers using cohort of 44 participants and evaluated balance of participants using BBS. The authors (Shumway *et al*.) identified fallers using the cut off value of 49 and reported a sensitivity and specificity of 77% and 86%, respectively

The study by Lajoie *et al.*[38] using 125 elderly participants found that scores of BBS is a significant predictor to identify fallers. A cut off score of 46 was reported as statistically effective and yielded a sensitivity and specificity of 82.5% and 93%, respectively. Another study utilised BBS to identify fallers with a cut off value of 45 reported a sensitivity of 53% and specificity of 93%.[36]

Despite the ability of BBS identifying fallers in multiple studies, there are conflicting reports on BBS ability. Studies by O'Brien *et al.*[39] and Riddle *et al.* [40] show that BBS does not have an ability to discriminate fallers from non-fallers.

2.2.3. Dynamic Gait Index (DGI)

DGI is one of the widely used clinical methods used to assess dynamic gait, balance abilities and risk of falling of an individual [31]. The DGI evaluates gait not only during the steady state walking but also while performing more challenging tasks. DGI consists of 8 tasks and each of the tasks in the range of 0 to 3 where 0 indicates poor performance and 3 indicates excellent performance. The scores given to the tasks sums up to a maximum value of 24. The tasks involved are gait on level surfaces, performing head turns in horizontal and vertical directions, walking at different speeds, turning 180^o during walking and stopping, stepping over and around objects and stair climbing. With the standard cut off value of 19, DGI have been applied in wide variety of conditions utilising participants with chronic stroke [41], Parkinson's disease [42], balance and dizziness [43] and relatively healthy old adults [37]to assess the gait. Moreover, DGI has been applied to predict fallers. Study by Shumway *et al*. [37] utilised DGI to predict fallers, with cut off value of 19, yielded a sensitivity and specificity of 59% and 64%, respectively. Similarly, Talia *et l.* [31] applied DGI on large cohort of 278 participants yielded a sensitivity of 92% and specificity of only 3% in classifying fallers with the cut off of 19.

2.2.4. Timed Up and Go (TUG) Test

TUG test is most widely used and accepted test for assessing functional mobility [32]. Illustration of TUG is shown in Figure 2.3: Illustration of TUG test.. At the instruction of the nurse observer, the participant is asked to stand from the chair, walk 3m at a comfortable pace, turn through 180^o, return back to the chair and sit down. The test performance is dependent on the chair height and 44-47 cms was the recommended chair height [44]. In this study the standard chair of height 46 cms was used. Nurse assessor observes the participant's performance and time to complete the test is measured using a stopwatch.

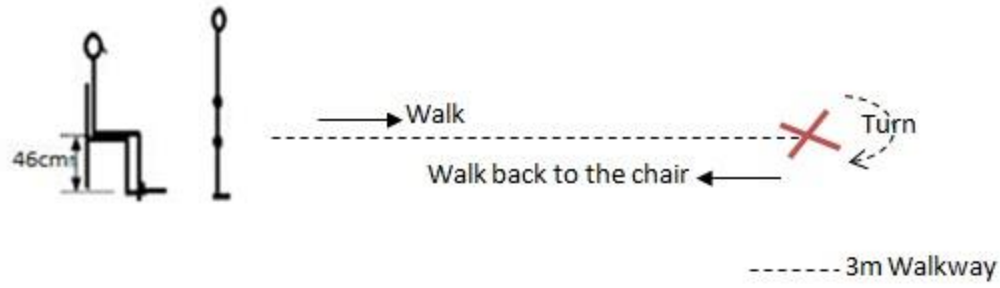

Figure 2.3: Illustration of TUG test.

TUG test is frequently used assessment methods to assess functional mobility and falls risk [45]. Podsiadlo and Richardson [32] evaluated TUG in 60 participants in a geriatric hospital and reported 30 seconds is the best cut off point to determine the functional independence of the participants of the study. TUG possesses high inter-rate reliability[1] in hospital in-patients [32] (ICC =0.99) as well as community dwelling older adults (ICC=0.98) [46] and also high test-retest reliability.

TUG has been reported in multiple studies, Shumway-cook *et al.* [47] evaluated TUG test in 30 community dwelling older adults and to identify fallers under single and dual-task conditions (carrying water, counting from 100 to 1 and subtracting 3- a cognitive task). It is reported that TUG is sensitive identifying fallers with sensitivity and specificity of 87% for 13.5s as the best cut-off. There are different cut off thresholds suggested by different studies, a study utilising 413 community dwelling adults suggested a cut value of 12s to segregate fallers from non-fallers [48]. The other, in-clinic study utilising 110 participants recommended a cut off 15s to identify participants with falls risk [49].Alexandre *et al.*[50], utilised 63 community-dwelling elderly adults performing TUG test, 12.47 s was determined as an effective cut off score which yielded sensitivity, specificity and accuracy of 73.7% , 65.8% and 68.3%,

[1] Inter rate reliability defines degree of agreement of the measurement among the raters.

respectively. Gunter *et al.* [51] undertook a study with 157 men and women. It was reported that TUG has an ability to classify fallers with an accuracy of 71.2%

TUG test was extensively studied in elderly adults [32],[52],[53],[47] also with variety of pathological conditions such as participants with Parkinson's disease [54], post stroke survivors [54] and patients with hip osteoarthritis [46] and fractures [55].

2.3. Ambulatory Assessment of Falls risk

For a long time, assessment of health through TUG and other clinical tests were observational in nature. Observational assessment takes long time, costly, intrusive, and not easy to study large cohort and prone to subjective judgement. One of the main drawbacks is the assessment of subjects with battery of tests in a clinical environment; this may hinder natural individual's performance in performing activities as described in the test protocols. Therefore a need for more practical and objective method of assessment became imperative. Developments of wearable sensors technologies allow assessing clinical tests through objective methods. Particularly, advances in the technology of Micro-Electro Mechanical Systems (MEMS) devices and 3-D packaging have driven the development of wearable sensors to record movement in both clinical and daily living environments.

Wearable sensors include pedometers, actometers, goniometers, accelerometers, magnetometers and gyroscopes. Pedometer is a simplest device which registers locomotion with a help of mass-spring system. It is a device which only counts the number of steps and is highly susceptible to noise. Although, pedometers are inexpensive, it is not possible to assess frequency, intensity of the movement and duration of activity. On the other hand, Accelerometers and Gyroscopes overcome the limitation of pedometers and allow measuring frequency and intensity of movements.

Nevertheless, Gyroscopes consume relatively more power than accelerometers hence cannot be used for long time.

Accelerometer offers a number of advantages in monitoring human activities. Accelerometers respond to frequency and intensity and allow determination of duration of activity. Accelerometers sense the gravitational acceleration at rest, this information can be used to determine the orientation of the sensor or the orientation of the body it is attached with. Recent developments in MEMS has resulted miniaturised, low power, less weight accelerometers which allows wearing it for long time without obstructing activities of the wearer. Therefore, accelerometers are emerging as practical, inexpensive and reliable methods of assessment in clinical and in daily living environment [56].

2.3.1. TUG vs. BBS and DGI

One of the primary objectives of this work is to develop a system that is feasible to assess falls risk of elderly adults who are aged 85 and over in their natural living environments. Particularly for participants over 85 years of age a careful selection of assessment method is needed. Moreover, the selected assessment method should be feasible and reliable for quantitative measurement using accelerometers. The following paragraphs compare the three widely used assessment methods (described in the section 2.3).

TUG, DGI and BBS all have proven valid and reliable. TUG test consists of single task where as DGI and BBS test comprises of multiple tasks. Rationally, one would argue that DGI and BBS are more comprehensive in nature and would yield better results. This is not true as BBS and DGI suffer from ceiling effects and was shown to suffer consistently in multiple studies [43], [57] and [58]. Nevertheless, it takes approximately 15-20 minutes to complete the tasks, hence would not engender quick assessment of falls risk. In view of elderly adults who are aged over 85 years, tasks such as sanding with one foot on front, reaching forward with out-stretched arm, stepping over and around objects etc. possess great danger to the participants.

TUG test requires participants to perform simple day to day activities such as walking, turning, sitting and standing. TUG test is relatively simple and would predispose to a quicker assessment than other two methods. Unlike BBS and DGI, ceiling effects[2] of TUG is not observed in any of the previous studies. Apart from being simple, TUG also has an ability to test multiple components of balance and mobility in a one single task, for an example: stand-to-sit is simple sequential combination of multiple tasks [59]. TUG consists of some of the activities of ADL such as walking, sit-to-stand which requires cognition function (planning and organisation); as a result, TUG may be associated to some degree to the executive function [45]. Association of TUG with the cognitive function is reported in several studies [60, 61] and inability to perform TUG has relationship with institutionalisation, impaired functioning and even death [59, 62]. TUG is measured in continuous scale whereas the other methods BBS and DGI are measured in ordinal scale. The ordinal ratings by the assessor is subjective, i.e. performance scoring could differ from individual assessor to another and therefore it is not standard and accurate. In addition, for a quantitative assessment using the ambulatory monitors such as accelerometers, TUG test offers more feasibility than others, as TUG comprises of multiple sequential tasks in a one single task.

[2] Ceiling effect- Variance in the predictor/independent variable no longer has an effect on the dependent variable.

British and American geriatrics societies [10] have recommended TUG test as a basic screening tool for falls risk owing to ease of use, reliability and its power to identify fallers in early health decline. To summarise, TUG test is simple, standard and shows feasibility for quantitative assessment of community dwelling elderly adults with ease. For the above reasons, TUG test is preferred over other two tests.

Objective of the current work is to utilise accelerometer as an ambulatory monitor on participants performing TUG test to predict fallers. The rest of chapter discusses the fundamental theory and background of the accelerometers, then reviews literatures on falls risk assessment using body worn sensors and finally discusses components of classification system used for identifying fallers.

2.3.2. Introduction to Accelerometer

Accelerometer is an inertial system which measures acceleration. A single-axis accelerometer can be modelled as the mass spring system attached to the solid support as shown in Figure 2.4 The mass attached to the spring undergoes displacement to the distance proportional to the force experienced (F) as explained by Hooke's law. It states that within the elastic limit of the spring (the greatest stress that can be applied to the spring before the onset of permanent deformation) the force applied to elongate/expand the mass spring system is equal to the product of displacement of the spring and the spring constant k. This is formulated as

$$F = -kx \tag{2.1}$$

The negative sign in the equation represents the Newton's third law of motion, which denotes that the deflection is due to the reaction force of the force applied.

The principle of operation of accelerometer can be mathematically understood by relating Hooke's law and Newton's second law of motion. Newton's second law of motion states that the force is directly proportional to the product of mass (m) and acceleration (a).

$$F = ma \tag{2.2}$$

Equating 2.1 and 2.2,

$$a = \frac{-kx}{m} \tag{2.3}$$

Equation (2.3) explains working of an accelerometer. It shows that the accelerometer basically measures force and, acceleration is derived from it.

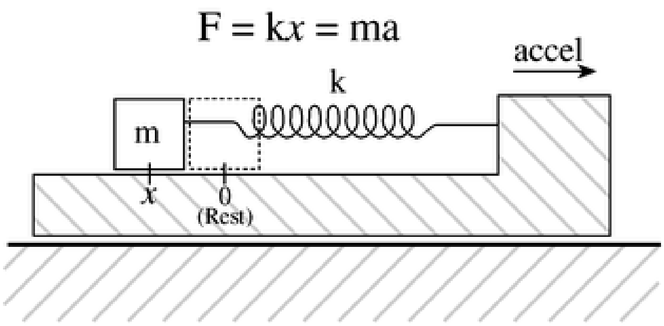

Figure 2.4 Accelerometer as a mass spring system.

Adapted from Analog devices ADXL50 [63].

2.3.3. MEMS Accelerometer

Advent of Micro Electro Mechanical Systems (MEMS) which combines electronics and mechanical components makes mechanical accelerometer available in the miniaturized form without compromising the effectiveness and also producing outputs in the electronic form. The basic working principle of the MEMS accelerometer is same as the mechanical accelerometers. A simple MEMS accelerometer has a micro machined seismic mass and cantilever beam which acts as the spring. When a force or acceleration is experienced, cantilever beam deflects proportional to the acceleration from the rest position this displacement is read by the analogue or digital readouts. Differential capacitive MEMS accelerometer is most widely used in current technologies such as mobile phones, gaming devices. There are many forms of MEMS accelerometers, such as piezoelectric piezo resistive and differential capacitive accelerometers. The capacitive accelerometers consists of mass suspended between two electrodes, the output is proportional to the deflection of mass between the two electrodes which is proportional to force or acceleration. The advantages are low power consumption higher sensitivity and faster response than other forms of MEMS devices. Differential capacitance form of MEMS accelerometer is utilised in the study.

2.3.4. Accelerations measured by accelerometers

Normal force is the force which acts perpendicular to the surface of any object. Normal force is an equal and opposite force acting on an object which prevents it from sinking through the surface placed provided that the surface is hard enough to deliver the reaction force. Earth surface is considered as the surface of reference, an object placed horizontal or parallel to the earth surface will apply the force equal to the product of weight and acceleration due to gravity and provided forces of friction are absent.

$$F = ma$$

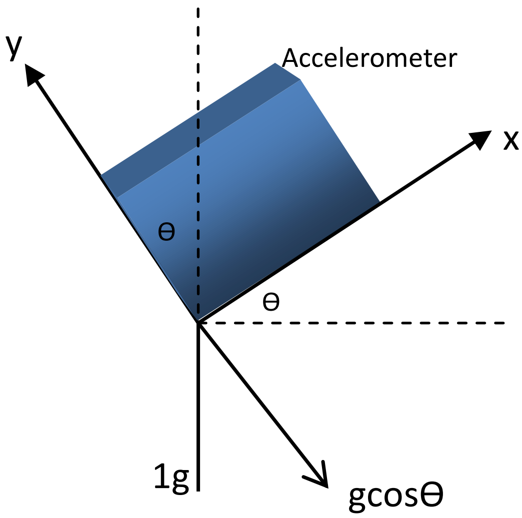

Figure 2.5: Forces acing on the accelerometer on the inclined surface. X, Y **are the axis of an accelerometer.**

Consider an accelerometer resting on the inclined surface as shown in the figure2.5. The force acting on the object neglecting the frictional forces is only the force of gravity. The accelerometer at rest measures only the normal force. Thus resolving the force of gravity due to the mass of an accelerometer, we obtain the cos function component responsible for the normal force. The following mathematical equation shows the acceleration measurements of an accelerometer at rest at any angle from the ground.

$$a = g\cos\theta \tag{2.4}$$

Case1: $\theta = 0,$ measurement axis is 90 deg from earth surface, $a = g$

Case2: $\theta = 90,$ measurement axis is 0 deg from earth surface, $a = 0$

Therefore an accelerometer placed on the horizontal surface (sensitive axis perpendicular to it) will measure acceleration equal to the acceleration due to gravity. In presence of additional external accelerations or forces the accelerometer, the output of an accelerometer is the sum of accelerations due to gravity and due to the additional external accelerations.

2.4. Literature on accelerometer for movement analysis

Accelerometers as a wearable sensor have been used in movement / gait analysis, falls detection and movement classification. Gait is an important factor which reflects one's ability to live independently, functional status [64] and risk of falls [65].Accelerometer can characterise gait patterns and thereby gait abnormalities can be detected. Parameters such as step time, stride length and stride symmetry extracted using accelerometer placed on the waist and thigh have shown detecting abnormalities in the normal gait patterns [66, 67]. It has been also shown that the parameters such as heel strike and toe off can also be detected which has the ability to describe abnormalities in gait and good predictor of falls [68].

Apart from gait analysis, with the accelerometer's ability to capture movements it has also been widely used for identifying different movements and activities. Accelerometers have been used to discriminate activities such as sitting, lying, standing, walking and even stair climbing [69-71].

Sit to stand and stand to sit shows functional status and an ability to live independently [72]. Narayanan et al. showed that there exists a moderate correlation between the accelerometer parameters extracted during sit to stand and stand to sit movements and falls risk [73].

Falls pose serious problems to elderly. In particular, for individuals aged over 65 years living in the community. Inability to get up after falls is major problem, this leads to dehydration, in case of any injuries the blood loss that occurs from the injury would even kill the person. Therefore falls detection systems were proposed. The falls detection systems identify falls when it occurs and generates an alarm to help can be reached. Accelerometer was used in many of the falls detection systems [5].

Although, falls detection systems are very helpful in reaching for help, the injuries and other effects of falls could not be prevented. Therefore, wearable sensor technology has advanced detecting abnormalities in earlier and preventing falls rather than detecting it. The following section describes the use of wearable sensors for falls assessment.

2.5. Literature on falls assessment using ambulatory monitors

In older cohorts, wearable sensors have been applied to the evaluation of standing balance [74, 75] falls risk assessment [74, 76, 77] and activities of daily living [78-80]. Accelerations measure vary depending upon the position of sensor placed and also on type of activity performed. In general, the acceleration magnitude increases from head to ankle which can be measured by three axes of an accelerometer [56]. In the past, sensors have been attached to the part of body which is being studied. For an example: Studies such as [81, 82] placed the sensor at the location of leg to study the leg movements. In an intention to study whole body movements, researchers placed multiple sensors at different locations of the body and some placed single sensor at location closer to the centre of mass of the body.

There are trade-offs in number of sensors used, cost, acceptability, usability and amount of information obtained. Utilising multiple sensors will permit collecting more information which will lead to more accurate recognition and classification. However, wearing multiple sensors for longer time would obstruct user activities of daily living, increases the cost and complexity of the system. On the other hand, single sensor is easy to wear, less intrusive to the user performing activity but would engender collecting lesser information than multiple sensors. The following survey demonstrates the literature utilising single and multiple body worn sensors, in evaluation of gait, mobility and assessing the falls risk of an individual.

Higashi *et al.* [83] utilised multiple wearable sensors (accelerometers and gyroscope) positioned at the upper back and thigh to quantitatively assess the TUG movements by evaluating on 20 hemiplegic patients. The authors developed algorithms to measure time taken from the individual components of the TUG test, i.e. time taken for sit-stand, walk, turn etc separately and compared it with the measurements with therapists.

Weiss *et al.* [84] conducted similar work utilizing a single accelerometer placed on the lower back to evaluate patients with Parkinson's disease using Timed Up and Go test. The authors utilised 32 participants, 17 with Parkinson's disease and 15 were control group. A number of measures was extracted from accelerometer and was shown that the measures have a value and serve compliment the prediction of disease progression and interventions.

Zamperi *et al.* [85] used TUG test with the five inertial sensors placed at various locations of the body such as shanks, wrist and chest. 24 participants were used in the study (12- PD and 12- healthy) and showed that the measures extracted from the sensors were able to detect the abnormalities in early-mild PD and can detect disease progression.

Similarly, Salariah *et al.*[86] used single packaged gyroscopes and accelerometer to assess balance and mobility of early-mild Parkinson's patients using TUG test. Authors' utilised 24 participants 12 with Parkinson's disease and 12 without, results suggest that use of sensor is of significant value and has potential for studying disease progression, where the stopwatch measure of TUG did not show any difference.

Similar study by L.Palmerini *et al.* [87] quantified motor impairment of Parkinson's patients using single accelerometer placed at lower back. Study utilised 34 subjects (20 Parkinson's patients and 14 control/healthy participants) performing TUG. The studies [83-86] focus on studying individual measures extracted from the sensors whereas [87] combined best features extracted from the accelerometer for classification.

Najafi *et al.*[77] used a miniature gyroscope placed at the chest to estimate falls risk of 11 elderly subjects and compared it to Tinetti balance scale. Three measures were extracted from the gyroscope was shown to be significantly correlated with the elderly falls risk.

Giansanti *et.al* [76] used both gyroscopes and triaxial accelerometer placed on the back at L5 to characterize 100 fallers performing balance tests. The measures related trunk kinematic parameters were extracted and showed very high discrimination ability 0f high falls risk participants with sensitivity and specificity greater than 0.939 and 0.930, respectively.

In recent studies, Narayanan *et al.* [73, 88] and Liu *et al*. [89] extracted a number of parameters from a single waist mounted accelerometer to estimate falls risk and validated the procedure against a physiological profile assessment. Narayanan *et al.*[73] undertook the study with 68 elderly adults and extracted number of measures from the accelerometer. The best selected measures are found to be correlated with the falls risk with the Pearson's correlation coefficient of ρ=0.81. Narayanan *et al.* work was improved by Liu *et al.* extracting many spectral measures and with automatic segmentation showed a correlation with falls risk of ρ=0.99 .

Greene *et al.* [90] utilized two kinematic sensors (tri-axial accelerometers and gyroscopes), placed on the shanks of the subjects, to generate parameters related to timing, gait and balance to retrospectively predict falls risk with the sensitivity and specificity of 77.3% and 75.9%, respectively.

2.6. Summary of falls risk assessment and problems with past works

Despite the previous studies described in section 2.5 showing the ability of body worn sensors identifying individuals falls risk, they share limitations: the data utilized by them were invariably collected in a clinical environment with small sample size and utilised manual segmentation of TUG sequence from whole recordings. The current study utilizes data collected in the home environment from 394 participants in the Newcastle 85+ Study [91], each with records of prior falls in the preceding 12 months and employs a semi-automated protocol to delineate TUG sequence from the whole instrument (accelerometer). By automatically delineating and analysing the TUG movement sequence, this system may translate simply to routine falls assessment in the home environment.

The present work is the first to assess the utility of a single wrist mounted accelerometer for estimating prior falls risk. The use of a single wrist mounted device with automated data processing and interpretation may be simple and convenient to apply and compatible with falls risk assessment protocols suitable for administration at home. The current study focuses on overcoming the challenges to automated TUG evaluation and seeks to improve prior faller identification.

2.7. Components of a classification system

The approaches of falls risk classification involve a multi-stage process. Broadly, the process involves feature extraction, feature selection and classification. Feature extraction basically involves dividing the sensor data into multiple window components and extracting features from each component. Followed by selection of highly discriminating features and finally these features are given to the classifier as an input for classification. Stages involved in design of classification system are shown in the Figure 2.5.

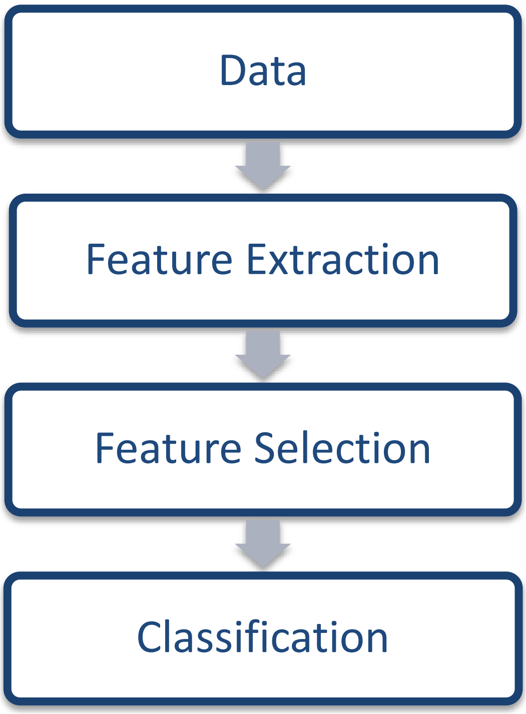

Figure 2.6 Overview of stages involved in design of classification system.

2.7.1. Feature Extraction

Feature extraction involves extracting features from the accelerometer that may be informative. Broadly, the features extracted are classified as heuristic, spectral and temporal. A brief outline of each of categories of feature extraction is given below:

Temporal Features: Temporal parameters are often statistical in nature; they include mean, median, mode, skewness and kurtosis [90]. Correlation-coefficient of different axes, different segments of the signal [92] and auto-regressive co-efficient [93] are all extracted. The temporal parameters are usually extracted from each of the window segments of the sensor signals. In particular to TUG test data, features such as walk time, number of steps, cadence and return time are widely extracted [90].

Spectral Features: Extraction of spectral parameters involves transformation of data into frequency domain using techniques such as Fast Fourier Transform (FFT). FFT represents frequency distribution and strength of frequencies present. There are many features that are extracted from the FFT of the signal; FFT is usually calculated using window segments of the signal. Some of the examples of spectral features are power [94], intensity, frequency-domain entropy [92], frequency ratio and magnitude ratio [89].

Heuristic Features: Different movement patterns result in varying amplitude of accelerometer outputs. Heuristic features aim to quantify the strength or amplitude of signal present and in turn using them to recognise and classify the movements. Heuristic features include Signal Vector Magnitude, Signal Magnitude Area (SMA) and Root Mean Square (RMS). These features are generally extracted after filtering the gravitational component present in the accelerometer signal.

2.7.2. Feature Selection

Feature selection is a technique of selecting the subset of features from the pool of features extracted, by discarding features that have less or redundant information. For an example: consider two groups, Group A: Less able to walk and Group B: Able to walk well. The selected subset of features extracted from originally extracted pool of features should show good association within the groups and high discrimination between the groups A and B.

Broadly, the feature selection techniques are divided into two categories: filter methods and wrapper methods. The following paragraph discusses the pros and cons of two methods.

Filter Techniques: Filter is one of techniques of discarding less informative features. The method in general works by ranking the feature through relevance score and features that score low are discarded. The advantages of filter technique are simplicity, quickness and being independent of the classification algorithm. Therefore, the ones the subset of features are selected it can be used in any of the classification algorithm. The disadvantages of filter technique are that they do not interact with the classifier, do not consider feature dependencies and hence sometimes leads to worse classification performance. Some of commonly used filter techniques are Fischer Discriminant Ratio (FDR) [95], class separability measures such as divergence, Bhattacharya and Chernoff bound and measures based on scatter matrices and Fast correlation based Feature Selection (FCBF)[95].

Wrapper Techniques: In order to overcome the disadvantages of filter techniques, wrapper methods were introduced. It is designed to interact with the classifier and account for feature dependencies. The feature selection procedure embeds the model hypothesis search within feature subset search. Search algorithm is usually enclosed around the classification algorithm to search for feature subsets. The best subset is validated using training and testing the data with the specific classification algorithm. Search algorithms include exhaustive search, sequential forward feature selection (SFS), sequential backward feature selection (SBS) and sequential forward floating feature selection (SFFS). The disadvantages are classification algorithm specific feature subset selection, high computation complexity and risk of over fitting compared to filter techniques.

There is third category of feature selection method known as embedded techniques; they can be seen as the searching for best subset in the combined space of classification algorithm and feature subset. They are less computationally complex than wrapper; however they are classification algorithm dependent.

2.7.3. Classifiers

The best selected features are given as the input to the classifiers. There are many variants of classifiers from low complexity statistical classifiers such regression classifiers, Discriminant Analysis (DA) to highly complex machine learning algorithms such as Artificial Neural Network (ANN), Decision trees (DT) and Support Vector Machine. The statistical algorithms are easier to implement and interpret results. Although, machine learning techniques have better classification capability it is harder to implement and interpret results. Moreover, for falls risk estimation in community dwelling, the algorithms that could be implemented in an on board processor would be beneficial. Hence, the statistical algorithms are better due to their low complexity. Regression analysis[3] is widely used in the falls risk estimation literatures. The following section introduces the simple and very common technique to measure linear relation called correlation co-efficient and then details about linear and logistic regression including underlying assumptions and interpretation of the fitted model.

[3] Regression Analysis is a method that is used to explain the relationship of variables using statistics.

2.7.4. Correlation Coefficient

Correlation defines the strength of linear association between two sets of variables. The two widely used correlation coefficients are: Pearson's correlation co-efficient and Spearman's correlation coefficient.

2.1.1.1 Pearson's Correlation Coefficient (r)

Pearson's correlation co-efficient measures the strength of association of a normally distributed variable sets. It is defined as the ratio of product of covariance to the product of standard deviations (SD) of the variable sets. r is usually given in the scale of +1 to -1, where +1 and -1 defines strong positive and negative correlation, respectively, and 0 defines no correlation amongst the variable sets.

The r of two variable sets x_1, x_2 is given by

$$r_{x_1,x_2} = \frac{\text{cov}(x_1, x_2)}{\sigma_{x_1}\sigma_{x_2}} = \frac{E(x_1-\mu_{x_1})E(x_2-\mu_{x_2})}{\sigma_{x_1}\sigma_{x_2}} \tag{2.5}$$

Where, cov is the covariance, E is the mathematical expectation, $\mu_{x_i} = Ex_i$ and $\sigma_{x_1}, \sigma_{x_2}$ are the standard deviations of variables sets x_1 and x_2.

2.7.5. Regression Analysis

Regression analysis is the common technique for studying relationship between input and output variables. In regression analysis, the inputs are defined as the predictors or independent variable and output variables are defined as the predicted outcome or dependent variables.

2.1.1.2 *Linear Regression*

Linear regression is a widely used technique to describe the relationship between an independent variable X and dependent variable Y given as a set of data points

(x_i, y_i). The relationship is expressed as the linear form as:

$$y_i = b_0 + b_1 x_i + e_i \tag{2.6}$$

Where b_0 (intercept), b_1 (slope) are the regression coefficients and e_i is the error term or residual. Residual is defined as the difference between actual Y_i and the point (x_i, y_i). The objective is to estimate the coefficients b_0 and b_1 in such a way that e_i is minimized. One of the widely used techniques for estimating unknown coefficients is the least square estimation method. This method aims to minimize the sum of the square error term or residual, it solution is given as follows.

$$S_r = \sum e_i^{\,2} = \sum_{i=1}^{n} [y_i - (b_0 + b_1 x_i)]^2 \tag{2.7}$$

Solving it for b_0 and b_1 by getting derivative, we get the following

$$\frac{\partial \sum e_i^{\,2}}{\partial b_o} = \sum_{i=1}^{n} 2[y_i - (b_0 + b_1 x_i)](-1) = 0 \tag{2.9}$$

$$\frac{\partial \sum e_i^{\,2}}{\partial b_1} = \sum_{i=1}^{n} 2[y_i - (b_0 + b_1 x_i)](-x_i) = 0 \tag{2.10}$$

Solving the above equations with b_0 and b_1 from

$$bo = \frac{\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_i^{\ 2} - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i y_i}{n\sum_{i=1}^{n} x_i^{\ 2} - (\sum_{i=1}^{n} x_i)^2} = \frac{\bar{y}(\sum_{i=1}^{n} x_i^2) - \bar{x}\sum_{i=1}^{n} x_i y_i}{\sum_{i=1}^{n} x_i^2 - n\bar{x}^2} \tag{2.11}$$

$$b_1 = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} x_i^{\ 2} - (\sum_{i=1}^{n} x_i)^2} = \frac{\bar{y}(\sum_{i=1}^{n} x_i^2) - \bar{x}\sum_{i=1}^{n} x_i y_i}{\sum_{i=1}^{n} x_i^2 - n\bar{x}^2} \tag{2.12}$$

Definitions of variance (σ_x^2) and co-variance $\operatorname{cov}(x, y)$ is defined as:

$$\sigma_x^2 = \sum_{i=1}^{n} (x_i - \bar{x})^2 = \sum_{i=1}^{n} x_i^2 - n\bar{x}^2 \tag{2.13}$$

$$\operatorname{cov}(x, y) = \sum_{i=1}^{n} (x_i - x)(y_i - y) = \sum_{i=1}^{n} x_i y_i - n\bar{x}\bar{y} \tag{2.14}$$

Using equations 2.15 and 2.14, b_0 and b_1 can be rewritten as:

$$b_1 = \frac{\operatorname{cov}(x, y)}{\sigma_x^2} \tag{2.15}$$

$$b_0 = \bar{y} - b_1\bar{x} \tag{2.16}$$

In order to assess the goodness of fit, Pearson correlation coefficient is used as defined in equation 2.5. When there is more than one independent variable is present, then the linear regression is called multivariate linear regression. Multivariate linear regression is an extension of linear regression and is described in the following form

$$y_i = b_0 + b_1 x_1 + b_2 x_2 + \dots\dots + b_p x_p + e \tag{2.17}$$

Where b_0 , b_1 to b_p are the regression coefficients of p independent variables. Many research problems, particularly the medical research studies are presented with analysis and prediction of dichotomous variables such as presence and absence of disease, predict an individual will fall or not and so on. For problems with dichotomous outputs linear regression cannot be used, as linear regression is limited to continuous dependent variables. To overcome this limitation Logistic Regression (LR) was introduced and became widely available through statistical software from 1980s [96].

2.1.1.3 Logistic Regression

Logistic regression is well suited for predicting categorical outputs or dependent variables with categorical or continuous predictors (independent variable). For an example, let's consider linear one dependent variable which is dichotomous (anaemia presence or absence) and one continuous independent variable (haemoglobin level), for this simplest case linear regression line would be as given in the illustration Figure 2.7 .

It is evident from the Figure 2.7 that it is difficult to use linear regression for dichotomous dependent variables, as extremes in the data plot do not follow linear trend and error distribution is not normal or constant. Therefore, in order to describe relationship between categorical dependent variable and continuous independent variable logistic distribution is used, for simple case of dichotomous dependent variable, relationship is given as:

$$\pi(x) = E(Y \mid x) = \frac{e^{b_o + b_1 x}}{1 + e^{b_o + b_1 x}} \tag{2.18}$$

Where, Y is the outcome of interest and $\pi(x)$ is the probability of the output when $Y = 1$ (presence of disease or event occurring) and $1 - \pi(x)$ is the probability of output when, $Y = 0$ (absence or event not occurring).

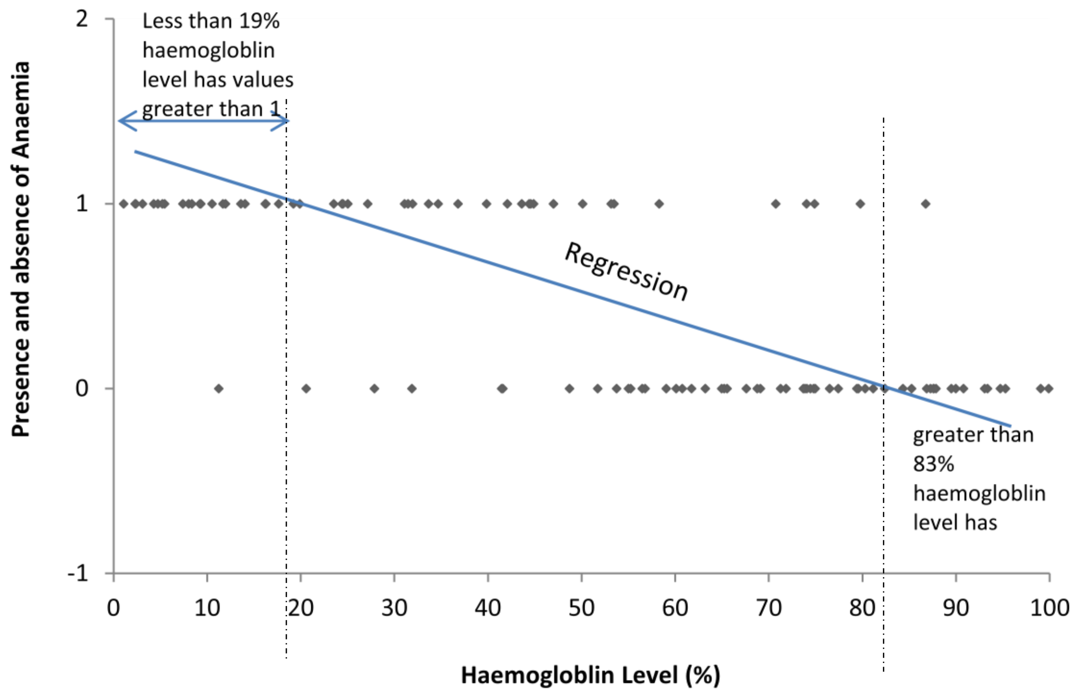

Figure 2.7: Illustration of simple linear regression with dichotomous dependent variable.

It can be seen that equation 2.18 is non-linear. Hence, Logit transform is applied to overcome this, and the simplest logistic model form is given by [97]

$$\ln(\frac{\pi}{1-\pi}) = b_0 + b_1 x \tag{2.19}$$

It can be seen that logit(Y) and x are linear. Similar to linear regression coefficients b_0 and b_1 for the above case has to be calculated. This simple case of LR can be extended for multiple predictors or independent variables as follows:

$$\pi(x) = \frac{e^{b_o + b_1 x_1 + b_2 x_2 + \ldots + b_p x_p}}{1 + e^{b_o + b_1 x_1 + b_2 x_2 + \ldots + b_p x_p}} \tag{2.20}$$

Similar to linear regression b_0 , b_1 to b_p are the regression coefficients of p independent variables and are commonly estimated using maximum likelihood function[98]. LR as the linear regression does not make normality assumptions of the independent variables or predictors. Most important characteristic of LR that made desirable choice in the medical studies are ease of implementation and interpretation of results.

2.8. Summary

The chapter describes the nature of human falls, its causes and effects. It is evident from the multiple literatures described that identifying risk factors of falls is a first step towards falls identification and prevention. Literatures of the past shown to have identified single risk factor and some have identified multiple risk factors of falls. Risk factors of falls allow identification of fallers and thereby permit offering interventions to prevent individuals from falling. Effectiveness and limitations of three widely used techniques BBS, DGI and TUG are compared and TUG is preferred over other tests. Need for quantitative assessment is discussed particularly focusing on benefits of quantitative assessment of TUG over past methods of objective measurement. The quantitative assessment of TUG is feasible through ambulatory monitors that can be worn over the body. Literatures that use ambulatory monitors with emphasis of community dwelling individuals are reviewed. Final sections describe the components of classifier system with the theory of logistic regression classifier which is used in the current study.

Next chapter describes the requirements of ambulatory monitor and discusses about the ambulatory monitor used in the study with the nature of the signals obtained from the monitor.

Chapter 3

3. Estimation of Falls Risk

3.1. Introduction

The chapter at first compares the methods (retrospective and prospective) of estimating falls. Subsequently, compares the constrained TUG test assessment and unconstrained free-living approaches of estimating falls risk. Secondly, the chapter presents the requirements of ambulatory monitors and presents the wearable accelerometer system (ambulatory monitor) used in the study. Later, chapter interprets the accelerometer signals obtained from accelerometer during TUG test. Finally, describing the methodology to estimate gravitational components thereby extracting the signals related only to the body movements.

3.2. Falls Categorisation

Falls have varying definitions, according to Tinetti *et al.* [14], a fall is defined as, "an event which results in a person coming to rest unintentionally on the ground or lower level, not as a result of a major intrinsic event (such as a stroke) or overwhelming hazard". The world health organisation [99] defines falls as "A fall is an event which results in a person coming to rest inadvertently on the ground or floor or other lower level". The study by Duncan *et al.* [100] excluded participants with falls, if they were from syncope, acute illness and while doing unusually hazardous activities in which even the healthy or fit person would fall. Shumway *et al.*[37] definition of falls is "A fall was defined as any event that led to an unplanned, unexpected contact with a supporting surface. We excluded falls resulting from unavoidable environmental hazards such as a chair collapsing."

Categorisation of falls is important and difference in categorisation leads to difference in falls rates and fall prediction. In general, falls are categorised as no-falls, single and multiple falls. 50% of fallers, fall repeatedly [11], 48% of the population report fear of falling and 20% report activity limitations [101] after a single fall. Fear of falling is reported to result in adverse health outcomes such as restriction in activities of daily living(ADL), decreased quality of life and depression [102], which in turn leads to increased risk of falling in future [103]. Therefore, single or the first fall has great implication to the falls and other adversities of health in future. In majority of falls studies [42, 53, 74, 90], given the importance of studying single fallers and also due to the limited number of participants, the multiple fallers is combined with single fallers category and commonly called as fallers as shown in the Figure 3.1.

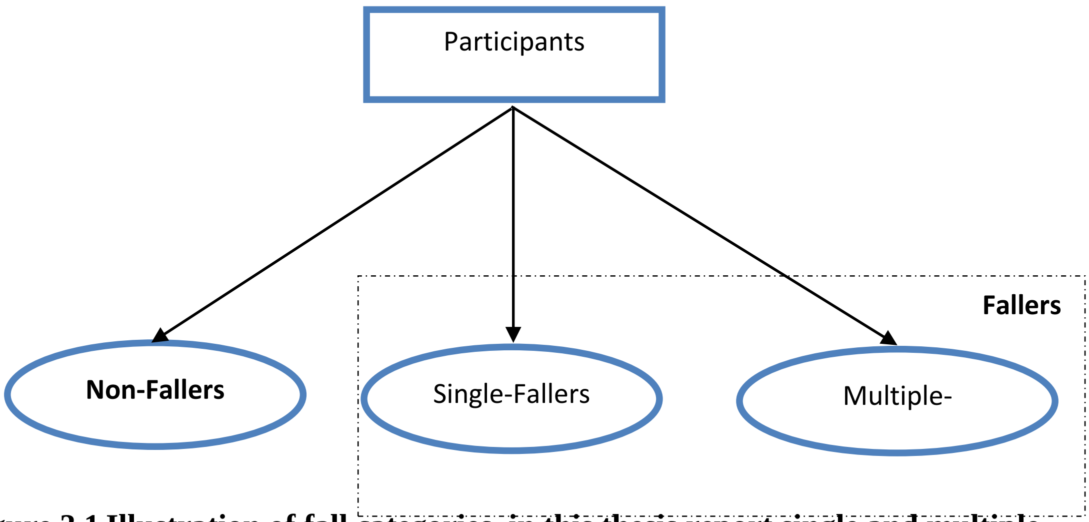

Figure 3.1 Illustration of fall categories, in this thesis report single and multiple fallers is combined and commonly called as Fallers.

3.3. Prospective vs. Retrospective Falls

Initially, qualitative methods of assessing falls using questionnaires, dairies and falls calendars were considered to be most feasible approach for assessment of falls. Later, more accurate and quantitative approaches such mobility assessment; balance scale and physiological assessment were introduced. Whether it is a qualitative or quantitative method, the falls could be studied either retrospectively or prospectively.

Prospective design involves assessing the participant using one of the qualitative or quantitative methods or both and following up the participant to obtain information regarding the falls. Follow up of the participant is usually performed using the telephone interview, asking the participant or the care giver to the fill the questionnaires. Such an approach is more reliable and considered as the gold standard approach to assess the elderly participant falls risk and to offer timely interventions.

Although, prospective design is more reliable, it requires large sample size for assessment and takes longer time for the reliable data collection. Moreover, it is crucial that, all the participants record falls in falls diaries and calendars as they happen, appropriately. In contrast, retrospective means of assessing falls can be completed in less time even for larger cross-section of participants. Falls risk model can be developed with the help of the falls history data and later the model can be used for assessment of falls prospectively. Although, falls history data may overestimate falls, it is a better tool than the pseudo-falls measure such as measuring balance scale (ordinal scale that is used by clinicians to rate the balance of a participant based on observation) estimating falls. One of the limitations of retrospective assessment is participant ability to remember falls completely. Participant remembering the circumstances of falls that took place would allow targeting factors that cause falls and to offer targeted interventions. So, there are limitations and effectiveness in both the methods of falls assessment.

The primary objective of this study is to develop automatic ambulatory falls risk assessment system using a wearable accelerometer that can be used unobtrusively by the elderly adults in the home living environment. The study in particular aims to develop a model using features extracted from the accelerometer signal to assess the falls risk of the elderly. Therefore, retrospective method of study is more amenable and feasible method for studying the falls evaluation. The retrospective method of falls assessment allows analysing the characteristics of the data and developing the falls estimation model. The developed model using retrospective data could be used for prospective falls estimation and studying the clinical significance of features extracted in the future.

3.4. TUG Test Vs Unconstrained Approach

Aim of the study is to estimate falls quantitatively in the home living environment. There are two different approaches in which data can be collected from the ambulatory monitors

1) Using the data collected from participant doing their activities of daily living without any constraints.
2) From participant performing constrained activities such as TUG test, continuous chair stands, alternate step, 10m walk etc.

The following section describes the advantages and disadvantages of both approaches.

In case of free living unconstrained approach, the participant wearing the sensor can perform their activities of daily living freely. The interaction with the sensor is very minimal (attaching and detaching the sensor). Nevertheless, there are number of disadvantages with the unconstrained data collection, they are:

1) Complexity in developing the signal processing algorithms becomes magnified. This is because participant can perform same task in variety of different ways, for an example, consider sit-to-stand, it can be from the standard chair, this can be also from couch or kitchen chair, both transitions are same but it is obvious that will be easy to stand up from the standard chair than the couch. Hence nature of the signals acquired by the sensor will be different which requires different and complex processing algorithms to recognise them.
2) The circumstances, environment in which tasks are done are not known, hence there is an intrinsic uncertainty in the collected data. This ambiguity in

collected data reduces the eminence of results obtained and moreover it does not allow targeted assessment of particular disorder.

3) To assess the falls risk of the participant, a relatively large amount of data collection is needed to identify the progression of falls risk.

In contrast, assessment using constrained task such as TUG test would overcome all the disadvantages described earlier. Task like TUG test, where participants are restricted to perform activity in a defined way, would reduce the complexity of the processing algorithms. Moreover, assessment can be targeted to the specific defects, for an example, assessing balance, stepping test can be used. Finally, participants are required only to wear sensor only when performing the tasks.

In light of aforementioned advantages, the constrained assessment of participant gait and balance is more reasonable. In this study, constrained retrospective assessment using TUG test is utilised to assess the falls of the participants from the data collected in the home environment.

3.5. TUG Test as an Assessment Method

Although, constrained assessment of participants offers major advantages than the data collected in the free living environment, great care has to be taken in selection of assessment tasks. In particular, for the system to be used by the older adults the ability of participant to perform assessment tasks safely is a major concern. Moreover, for a system to be used in a free living unsupervised living environment, all types of movements cannot be performed as it is potentially dangerous. For example, for to assess the gait of the participant, Dynamic Gait Index test can be followed, this involves tasks such as participant performing a balance task of standing in with one leg and stretching forward. Such a task appears to be very dangerous to the participant.

Therefore, selected movement task should be simple and also possess less safety risk to the participant.

Other than safety constraints, selecting simple movement task offer advantages, as it is easy for the participant to repeat the task, does not require much of the thought process and would be more compliant with the participant.

Reliability of the test, test/retest reliability is a measure of consistency of the test. A task or test with good test/retest reliability will yield same results when the test is performed later in time in same way with all the previous conditions are met. In case of falls estimation, if the test does not have good test and retest reliability the results of the test cannot be compared from one time to another and also from one individual to another. Hence, it is important that the selected movement task/test have good test/retest reliability.

Time taken to perform the task, is an important factor to be considered in selection of movement task. Less the time taken more advantageous it is, as it allows quick assessment and also will be more accommodating by the participant.

Of all the factors discussed earlier, the most important one is that, the selected movement should be able to provide information to estimate falls. With the all the qualities mentioned earlier, if the selected test does not have an ability to provide information regarding the falls, then the selection of test would be meaningless.

Considering all the factors that are discussed above, TUG test is selected as the assessment task. TUG test is simple, reliable, has ability to offer information regarding falls and automation of the test is also amenable. The other advantages of the TUG test are previously presented in the section 2.4.1.

3.6. Estimation of Falls Using Accelerometer

Having discussed the benefits of quantitative and automated assessment of falls, an approach has been taken to estimate falls of the participant using single wrist mounted accelerometer in this study. A healthy set of literatures showing the ability of an accelerometer to assess the functional mobility, gait and obviously falls risk of the participant are described in section 2.5 of chapter 2. A number of features could be extracted from the accelerometer signal and these features may have an ability to estimate fallers. Next section describes requirements of wearable inertial system to assess fallers in home living environment and accelerometer used in the study.

3.7. Requirements of the Wearable System

The requirements of wearable accelerometer system vary depending upon environment (clinical or home) and usage (supervised or unsupervised). In case of, clinical supervised setting, there is a higher flexibility, as the user interface such as mounting the device on body, switching the device on/off, annotations, removing the device are taken care of by the supervising individual. On the other hand, for a use in an unsupervised home living environment, the user interfaces has to be made as simple as possible. In particular, for elderly individuals, user interfaces and comfort of using the device is the primary requirements. This means that the device has to be small, lightweight as possible, easy to power on/off and have provisions to wear and remove easily.

Moreover, the accelerometer should be capable enough to capture different strengths of accelerations generated during the assessment task. The accelerations generated during the movements differ depending upon locations of the body and upon the activity being performed [56]. In general, the accelerations magnitude increases from head to foot. It is estimated that almost all of the measured body movements are with 20 Hz and 99% of the accelerations energy even in gait is constrained below 15 Hz [104]. Therefore, it is necessary that the accelerometer system is able to measure frequencies from 0- 20 Hz.

To summarise, the requirements of wearable accelerometer system are, it should be comfortable, easy to use, have enough bandwidth and sensitivity to measure the accelerations generated by the body movements

3.8. GENEA Accelerometer

The GENEA (Gravity Estimator for Normal Everyday Activity) tri-axial accelerometer is developed by Unilever Research (Colworth Science Park, Sharnbrook, Bedfordshire MK44 1LQ). GENEA contains seismic acceleration sensor from STM microelectronics (LIS3LV02DL), Geneva, Switzerland. GENEA accelerometer is small with dimensions of 36mmx30mmx12mm (LxWxH) with the splash proof casing and weighs only 16 grams. GENEA accelerometer's top and side views are shown in the Figure 3.2.

All the three axes have a bandwidth of 640 Hz and ability to measure accelerations up to ±6G (1G = 9.8ms^{-2}). It has internal storage space of 500MB, which can store up to 8 days of data in 12-bit resolution. GENEA comes with software which allows configuring the sensor with the sampling frequency (10 - 80 Hz) and also assists downloading the stored data for processing. GENEA accelerometer and screen shot of accompanying software is shown in the Figure 3.3 and Figure 3.4. In this study, sampling rate of 80Hz is used as the frequency of body movements are within 20 Hz

[105] and as it is the maximum sampling rate that can be configured using the software.

With respect to the requirements stated in the previous Section3.1, GENEA is small, very light, and comfortable to wear, with adequate abilities to measure accelerations generated by the body movements and therefore selected as an ambulatory monitor to use in the study.

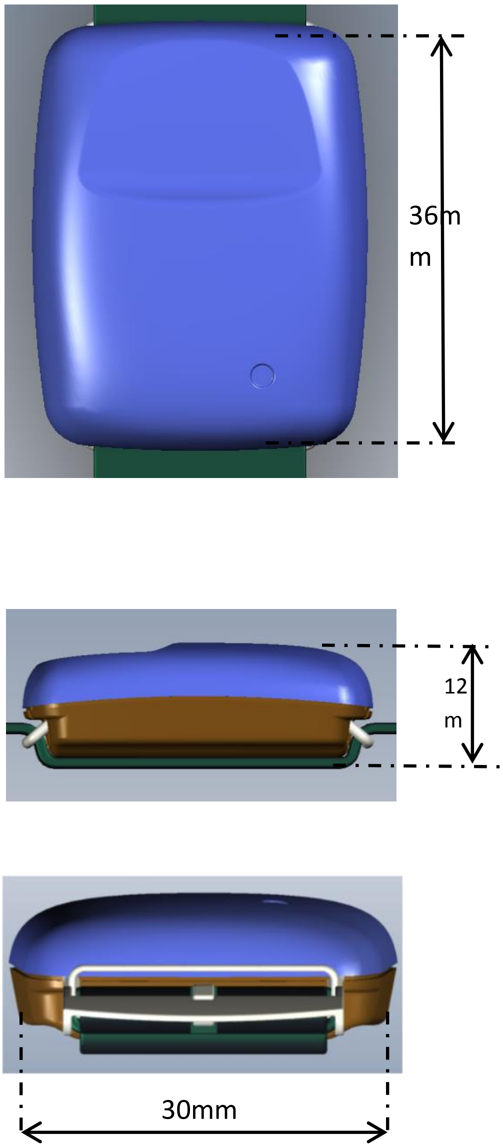

Figure 3.2: GENEA accelerometer showing top and side views

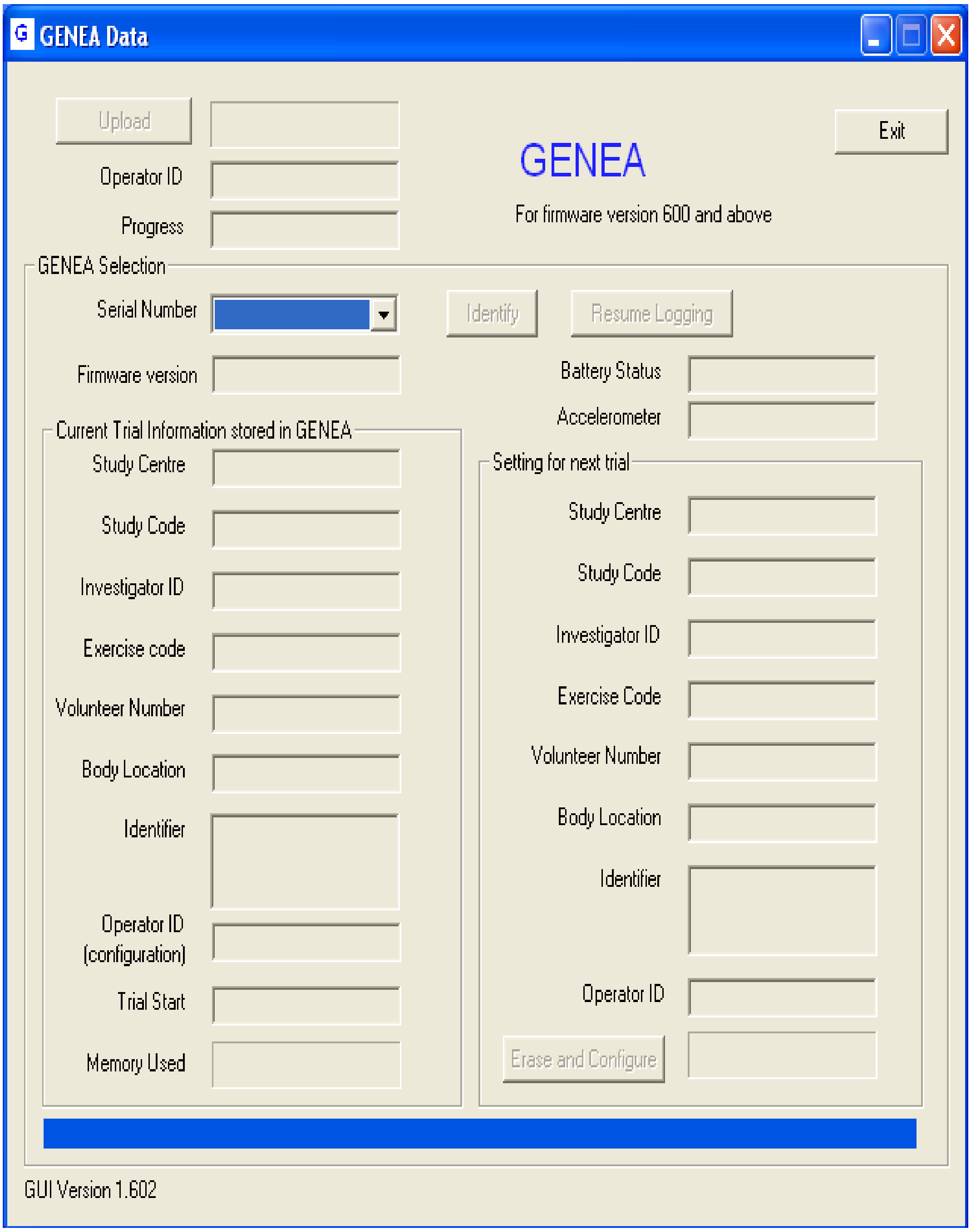

Figure 3.3: GENEA software screen shot, it allows configuring the data collection, downloading and erasing the stored data in the memory of the accelerometer.

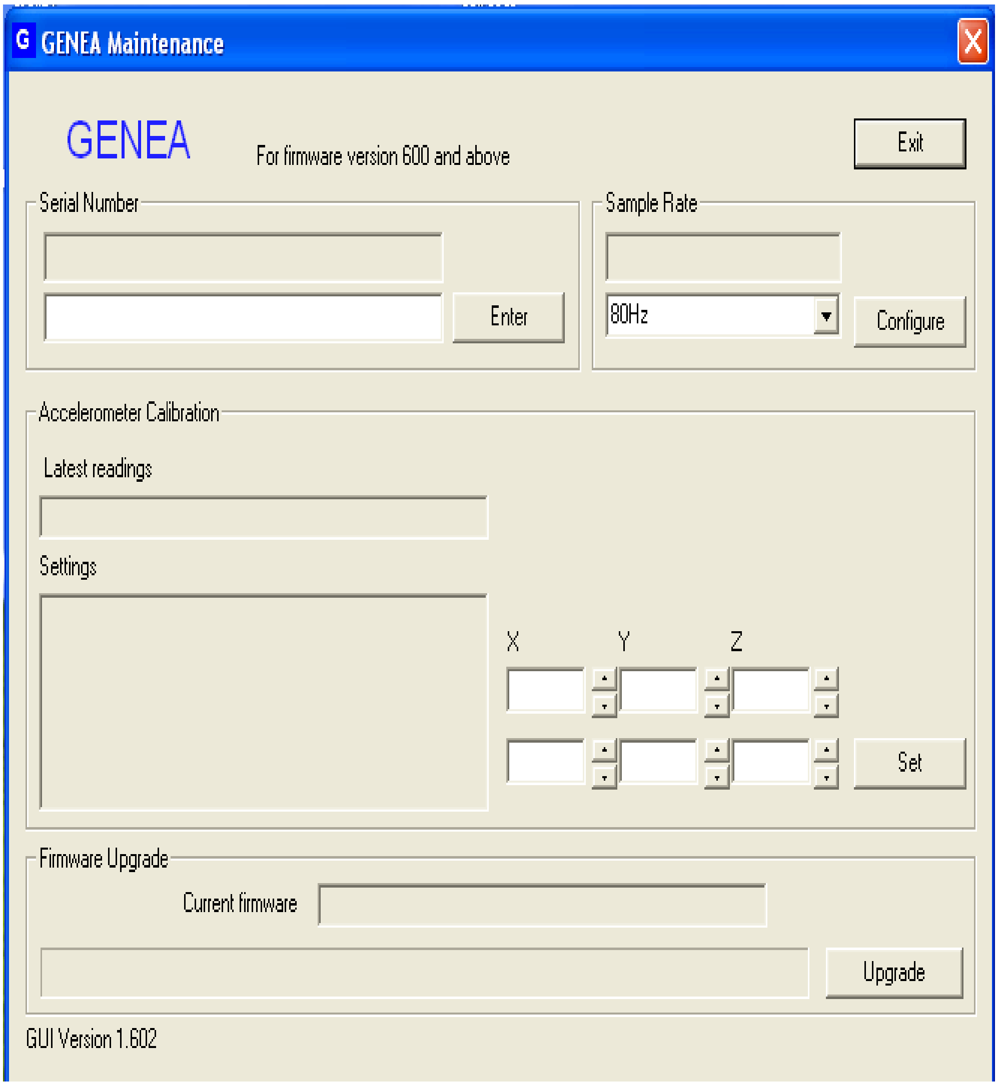

Figure 3.4 : Screen shot of accompanying software which allows configuring sampling frequency and setting an offset for the accelerometer.

3.9. Accelerometer Placement

In the past wearable sensors are placed at various locations to collect information related to activities being performed. The location of sensors placed should be comfortable and unobtrusive to users performing activities. In many of the past studies, position of waist is chosen for sensor placement as it may acquire the whole body movements being closer to centre of centre of mass [106]. Apart from waist, sensors have been placed at various locations which includes shanks [90] , chest [107], ankle [108], wrists [109-112] and thigh [113] showing the alternate locations for sensor placement. Although, most of literatures in the past have placed the sensor at the waist location, its non-compliance with participants is also shown in multiple studies [114-116]. In addition, It is documented that during changing clothes, sleeping, participating in contact sports and while attending occasions, the waist mounted sensor had to be removed, which resulted in considerable reduction in information obtained [117].

For older adults, especially over 85 years of age, compliance of the sensor placement becomes vitally important. Placing sensors over the waist would be uncomfortable and hinder their natural movements. Wrist offers higher universal acceptance and proves feasible way forward for acquiring data regarding movements from the individuals of this age. Wrist mounted GENEA accelerometer's validity is shown in [110]. Studies by Phillips *et al.*[109], Esliger *et al.*[110] demonstrated that wrist shows a good criterion validity in assessing physical activity, Vanhees *et al.* [112] showed the accuracy of the wrist mounted accelerometer is comparable to the location of waist and its acceptance in estimation of daily energy expenditure. In light of such findings, we attempt to investigate the wrist mounted accelerometer in assessing falls risk of the community dwelling elderly adults.

3.10. The Accelerometer Signal

It is vital to understand the nature of the signal obtained from the GENEA accelerometer, before extracting features from it. This section gives a summary of the nature of the signals obtained from GENEA accelerometer.

The GENEA accelerometer has three sensing axes mutually orthogonal to each other. Accelerations by three axes are measured relative to the position of the sensor placed, not to the global reference frame. In this study accelerations are measured in relative to the position of the wrist.

The accelerometer’s signals comprises of three components, they are:

1. Gravitational component.
2. Accelerations due to the body movements.
3. Intrinsic and extrinsic noise.

Intrinsic sources of noise are mostly electronic noises that occur internally during manufacturing the sensor. Extrinsic sources are accelerometer movement due to unintentional contacts with external objects, displacement of accelerometer after attachment etc. In this study, external sources of noises are considered absent and also noises due to the intrinsic source are neglected. Therefore, the accelerations measured by the accelerometer comprises component of body and gravitational acceleration.

3.11. Pre-processing of gravitational components from body movements

At rest, the accelerometer sensitive axis measures the accelerations equal to $g\cos\theta$, as shown in the Figure 2.5 as described in the section 2.3.4.

Therefore, at rest, the sensitive axis perpendicular to the gravitational vector (g) will measure 0g and will measure ±1g when parallel to the g. The body component comprises of the accelerations which is the projection of body movements to the measurement axis. At rest, the body component of the accelerometer measures zero and output is only due to the gravitational component. As the body moves, the accelerometer will acquire both the information related to the gravitation as well as body movements.

The body component and gravitational component of an accelerometer signal acquired during body movements is inseparable and overlapped in the time domain of the signal. In frequency domain, the gravitational components are of 0 to few hertz and body components range from 0 to 20 Hz. Therefore, the information is overlapped also in frequency.

The objective of the current study is to characterise the body movements during TUG test to estimate falls risk of the participants. Therefore, body components have to be separated from the gravitational components before characterising the movements related to body. A proven and well-known method of approximating body and gravitational methods is through filtering [118, 119]. A high-pass filter is implemented with fourth order elliptical impulse response, cut off frequency of 0.25 Hz [78], Pass

Band Ripple[4]: 0.01, Stop Band Attenuation[5]: 100db to estimate the gravitational components. Body components are approximated by subtracting the estimated gravitational components from the raw accelerometer recordings. Figure 3.5 illustrates this process. The filtered signal is used in all the following section which describes feature selection methodology.

[4] Permitted amount of amplitude variations in the pass band.

[5] Minimum permissible range of amplitude in the stop band that are higher/lower than the desired amplitude.

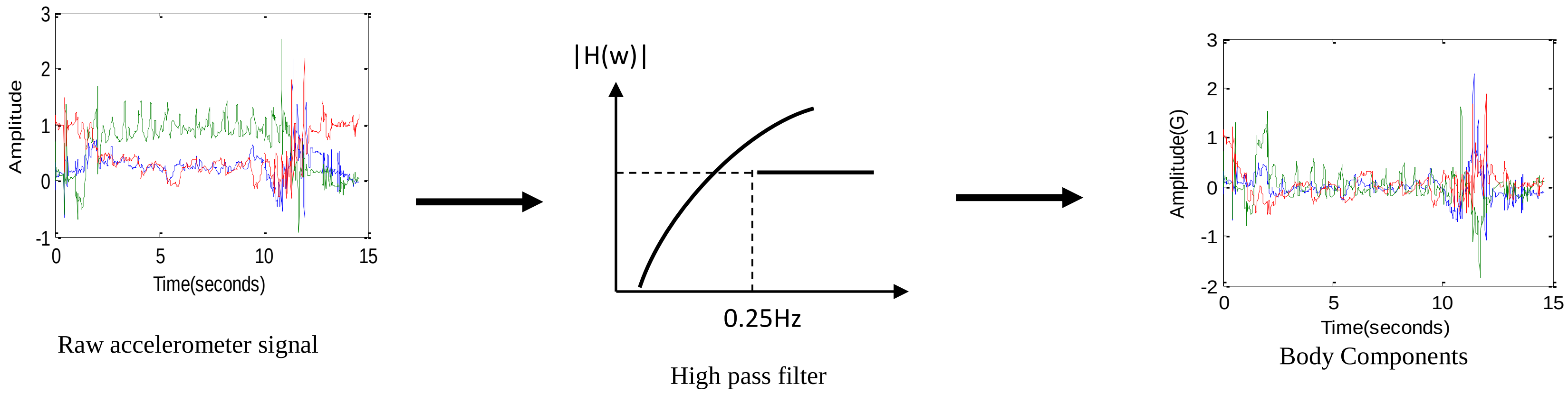

Figure 3.5 Delineation of body components using high pass filter from raw accelerometer signal

3.12. Data Collection

This study is nested within the NE85+ Study, a longitudinal study of health and ageing [12, 120]. The participants included in the study were aged around 85 years during the recruitment which began in 2006. All (63) of the general practices in North Tyneside National Health Service (NHS) Primary Care Trusts were requested to participate in the study. General practitioners of the agreed trusts (83% of general trust agreed), were sent an invitation to individuals (who had registered with them) to participate in the study living either in home or in institutions. Individuals who posed a safety concern to perform the study's activities (solely under a supervision of a visiting nurse) and those who with end stage terminal illness were excluded. Detailed multi-factorial health assessment was conducted at baseline (participants were allowed to decline described protocols) in the participant's usual place of residence by a visiting clinical staff. Following baseline assessment (Phase 1: 2006-7, n=854), NE 85+ Study participants are re-assessed at 18 months (Phase 2: 2007-9, n=631) and again at 36 months (Phase 3: 2009-10, n=484). Participant loss between phases 1 and 3 is mainly due to death (62.7%, 232/370) with the remainder due to drop out. Participants answered the questionnaire regarding the falls in last 12 months, in case of an inability of the participant, caregiver answered the questionnaire.

Ethical approval was obtained from the Newcastle and North Tyneside 1 Research Ethics Committee (reference number 06/Q0905/2). Written informed consent was obtained from participants and where people lacked capacity to consent, for example because of dementia. Further information on ethical approval can be found in [120].

3.13. Evaluation of TUG using Wrist mounted Accelerometer

Following the collection of data regarding the falls in past twelve months, evaluation of participants with the TUG test took place at the participant's home. Staff or nurse visited participant's home or their daily living environment, as the standard procedure equipment such as standard chair, measuring tape, marker and stop clock was carried. The same standard set of equipment was used in all the participants home. An unobstructed straight pathway was selected to carry out the test. Marker was placed three meters away from the chair, as shown in the

Figure **3.6**.

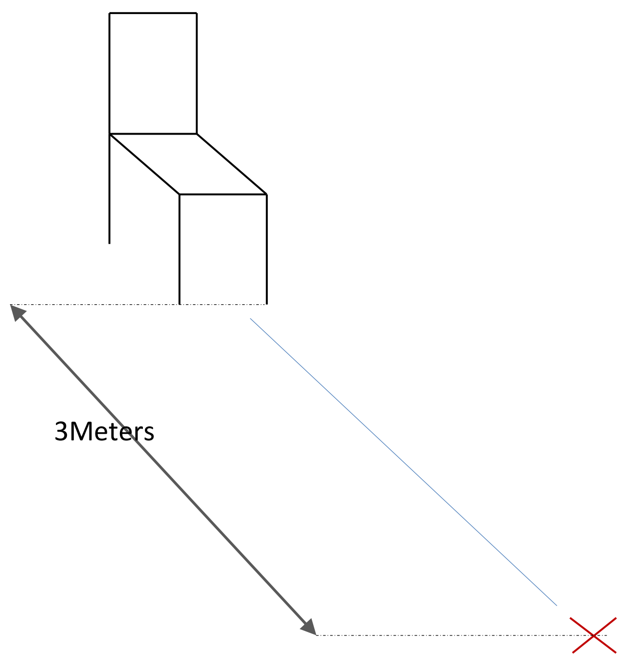

Figure 3.7 Illustration of TUG test.

Participants were asked to wear the accelerometer on their right wrist before the performing the test. Participants wore the accelerometer on their right hand wrist as shown in Figure 3.7. This was set as the standard protocol for wearing the accelerometer in order to maintain uniformity in measurements. Accelerometers used are all configured to acquire data with sampling frequency of 80Hz.

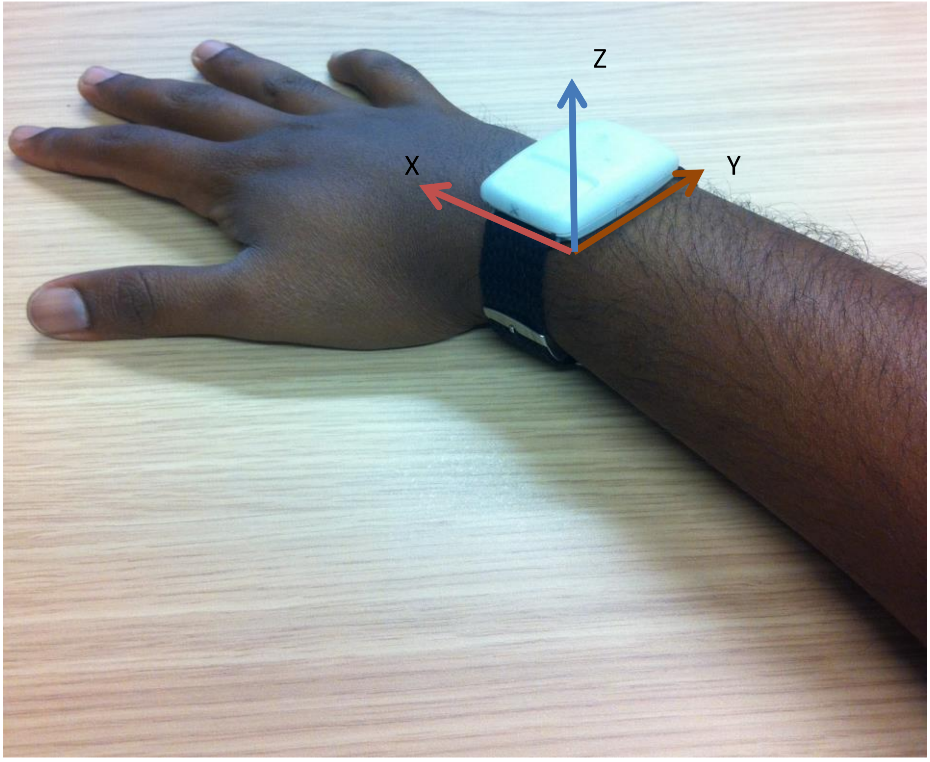

Figure 3.7 Shows the wrist mounted GENEA accelerometer

All the instructions regarding the TUG test were given to the participant before the test. They were asked to walk in their natural comfortable pace. Use of walking aid was permitted during the test. The test is carried out under the supervision of the visiting staff. The supervising staff would also time the test using the stop clock.

Data collected were transferred to a computer, offline using the software described earlier in section 3.8. The sample TUG test obtained is shown in the Figure 3.8 .

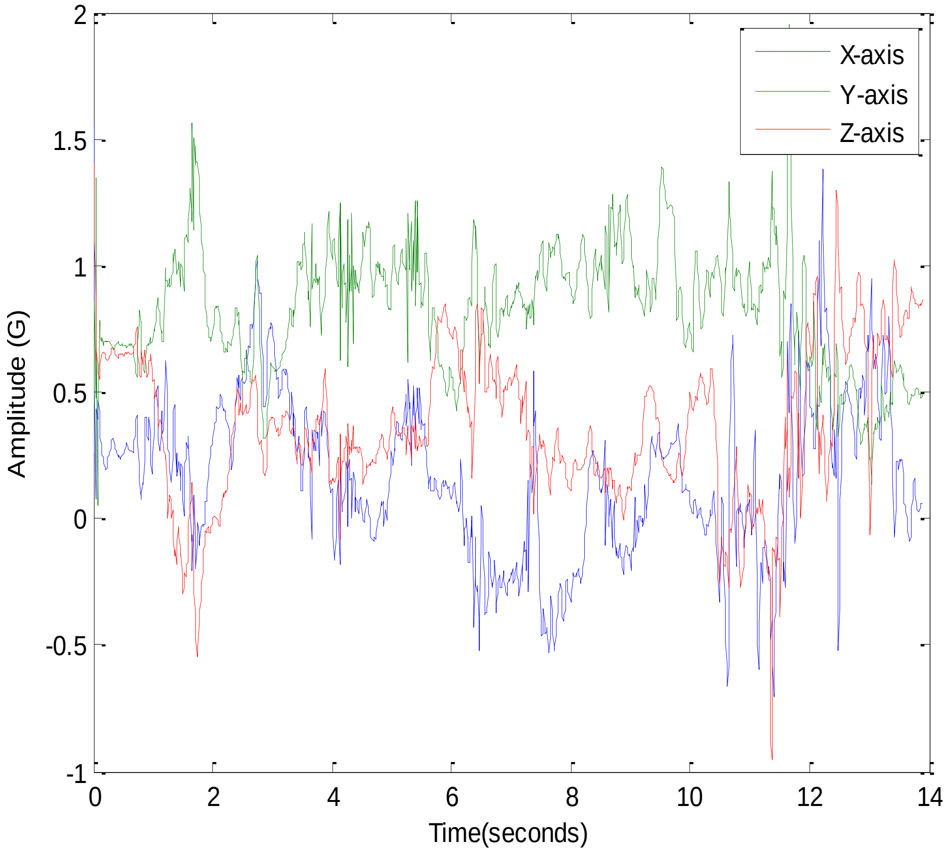

Figure 3.8 Example of TUG test accelerometer recordings.

3.14. Conclusion

The chapter described the requirements of the assessment task and wearable ambulatory monitor for the estimation of falls in home environment. TUG test is chosen as the assessment task as it is reliable, simple, quick and safe as the task comprises of components that are performed in the daily activities of living. GENEA accelerometer is chosen as the ambulatory monitor as it satisfies all the requirements that are necessary to capture the movement signals during the selected TUG task, apart from being small, lightweight and easy to wear. The signals obtained from the GENEA accelerometer are described. The accelerometer signals have two components: the gravitational accelerations and acceleration due to body movements. A filter is designed to approximate the gravitational components and thereby extracting only the component related to the body accelerations. The following chapter presents the protocol implemented for automated falls risk estimation and methodology of features extraction from the TUG test signals of the accelerometer.

Chapter 4

4. Methodology

4.1. Introduction

Automatic falls prediction system not only enables to broaden the elderly falls estimation beyond the clinical setting it also allows quicker and objective estimation. With the increasing rate of life expectancy, the need for an automatic system for falls detection is imperative. Literatures of falls estimation using inertial sensors are described in Chapter 2, Section 2.4. Although, the past studies showed the feasibility and validity of inertial sensors for falls estimation, one of the common limitations of all the past studies is the failure to extract the TUG test movement sequence automatically from the complete sensor recordings (Incidental data and actual TUG sequence). This does not make the system automatic, where manual segmentation of movement sequence from whole recording is required.

This chapter describes the protocol implemented in an attempt to extract the movement sequence from the complete sensor recording algorithmically. Following on automatic sequence extraction, it describes the methodology of features extracted from the movement sequence. Finally, explains the need for feature selection and employed methodology of feature selection.

4.2. Automatic Falls Estimation

Automatic falls estimation aims to minimise user and external user input in estimation of falls. Once the selected movement sequence is performed by an individual, the system deployed should function on its own with minimum assistance in assessing the falls. The following section describes the methodology of falls estimation and the method to automate falls estimation.

The concise flowchart of methodology of falls estimation using a wearable sensor is given in Figure 4.1. All the components described in the Figure 4.1, other than participant's wearing the sensor and performing the assessment can be automated.

In order to automate the process the first step was to delineate the movement sequence from the complete recordings. This is because once the monitor is powered on it starts collecting data. Hence the monitor would have recorded the data relevant to attaching the device and any other movements that are performed before the actual assessment task. Therefore, it was necessary to delineate the movement sequence from the incidental noise thereby extracting features only from the movement sequence.

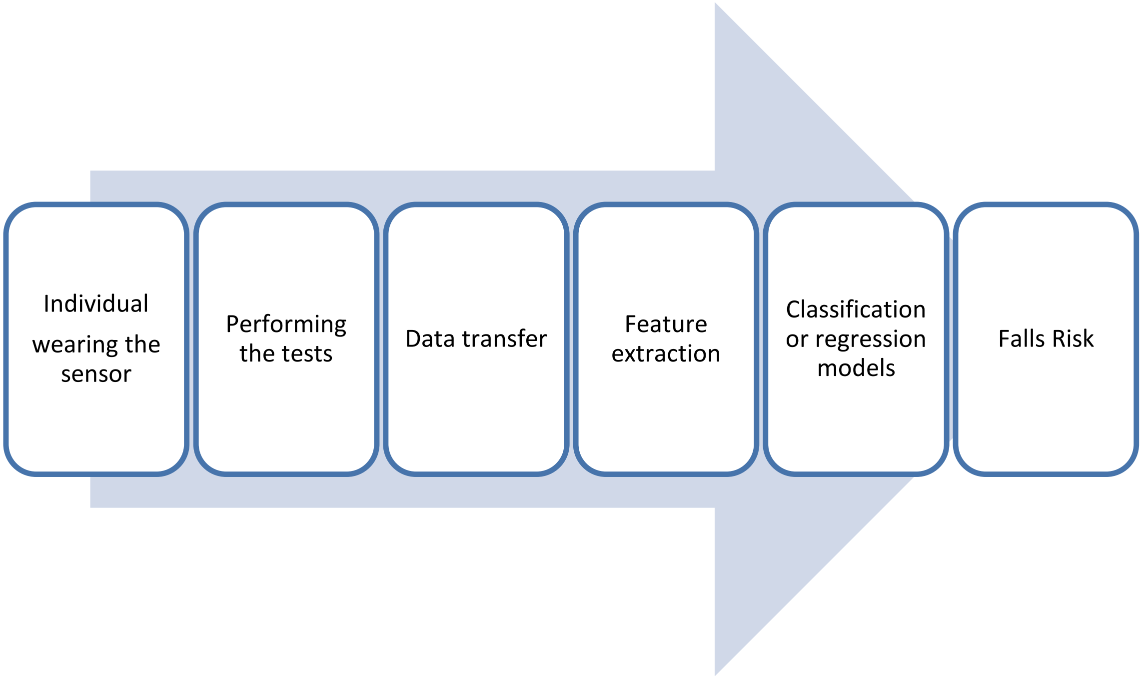

Figure 4.1: Method of falls risk assessment using wearable sensor

In the past, the movement sequence had been delineated manually using the start and end annotations (by the supervising staff using a software). Manual segmentation of assessment sequence does not allow estimating falls automatically. This procedure does not make the system automatic, prolongs the processing time and inhibits falls estimation in the community dwelling environments as a result delineation of movement sequence is essential.

Delineation of movement sequence can be done before or after the data transfer as shown in Figure 4.2. There are some trade-offs: with both of the methods. In the case of delineating the movement sequence before the data transfer- the amount of data transferred will be significantly less and would enable longer operation of the battery. However, this requires powerful processor to be embedded in the system to delineate the movement algorithmically. In contrast, if the automatic delineation procedure is done in a remote location after the data transfer then a larger amount of data has to be sent which reduces the battery life, but does not require powerful embedded processor with the sensor. This study delineates the genuine movement sequence after data transfer to the computer.

Previous studies have invariably focused on automating the extraction and segmentation of components related to body movements and movement sequence as a pre-processing step before feature extraction. This does not automate the assessment as the delineation of movement sequence from the whole of recording has to be made prior to pre-processing step. The delineation of movement sequence automatically will make the system completely automatic which enables an individual to use in home living environment easily.

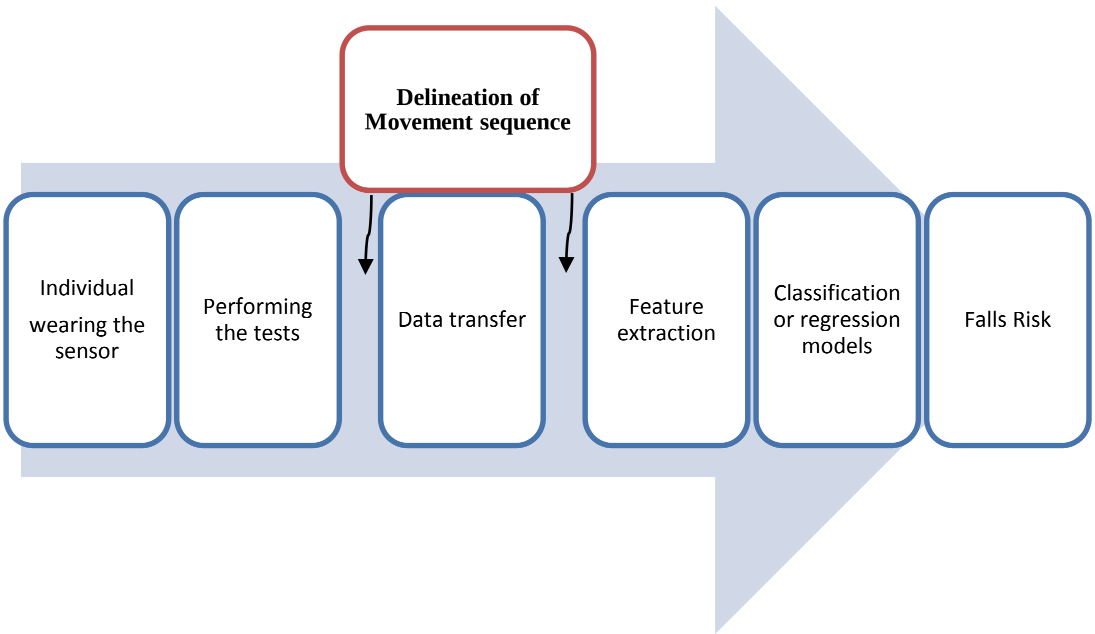

Figure 4.2 Delineation of movement sequence, before or after data transfer for completely automatic falls risk assessment.

This is the first study investigating delineation of TUG movement sequence (automatically) from whole recording, using the data collected from home environment. A protocol was implemented in an attempt to assist the automatic isolation of the TUG sequence and thereby estimating falls automatically

4.3. Identification of Taps for Delineating TUG sequence

To assist the automatic isolation of the movement sequence the visiting clinical staff would bracket the test sequence by deliberately tapping the device two or three times at the start and end of the test sequence. These taps signatures in the recording have to be identified algorithmically delineating the movement sequence from the whole recording. The following section presents the detailed methodology of delineation procedure.

A simple threshold based algorithm identifying the taps signatures makes it easy to implement and reduces the processing complexity. Appropriate thresholds for identifying taps' signatures have to be determined; to reduce false sequence recognition from the whole recording. To understand the characteristics of taps signatures and incidental noise, participants' recordings are studied through visual examination. Through visual examination the following were deduced

1) Noise peaks resembling individual tap signatures are generally lower in amplitude than actual tap signatures.
2) Noise peaks are either closer or further from each other than the actual taps signatures.
3) The protocol demands that three taps be made, however protocol is not followed at times and only two taps are only made.

4) Some of the taps are not made with enough force (accelerations); hence taps amplitude is very weak.
5) In some of the participants' recordings either the start or end taps are only made.
6) In few recordings, the taps are not made at all.
7) In other few, the taps are made but movement sequence is not performed and later the taps are again made and sequence is performed.

The algorithm was developed considering all the above points except for points 5 and 6. The participant files which fell under points 5 and 6 were considered as not having adhered to the protocol correctly. The participant's recordings which did not adhere to the protocol correctly were excluded from automatic delineation algorithm. Out of 395 files in analysis, 299 (75%) files adhered to the protocol and the remaining were excluded from automatic delineation of movement sequence.

The Figure 4.3 shows the sample plot of whole accelerometer recording with annotations of actual sequence and incidental noise. Considering the characteristics of the taps two different thresholds are set as following

1) Threshold for a minimum amplitude for the tap signatures, as the noise peaks (which resemble taps) are lower in amplitude.
2) Thresholds for minimum and maximum distance between the taps shown in Figure 4.4.

The TUG movement sequences with the taps (numbered) are shown in Figure 4.4.

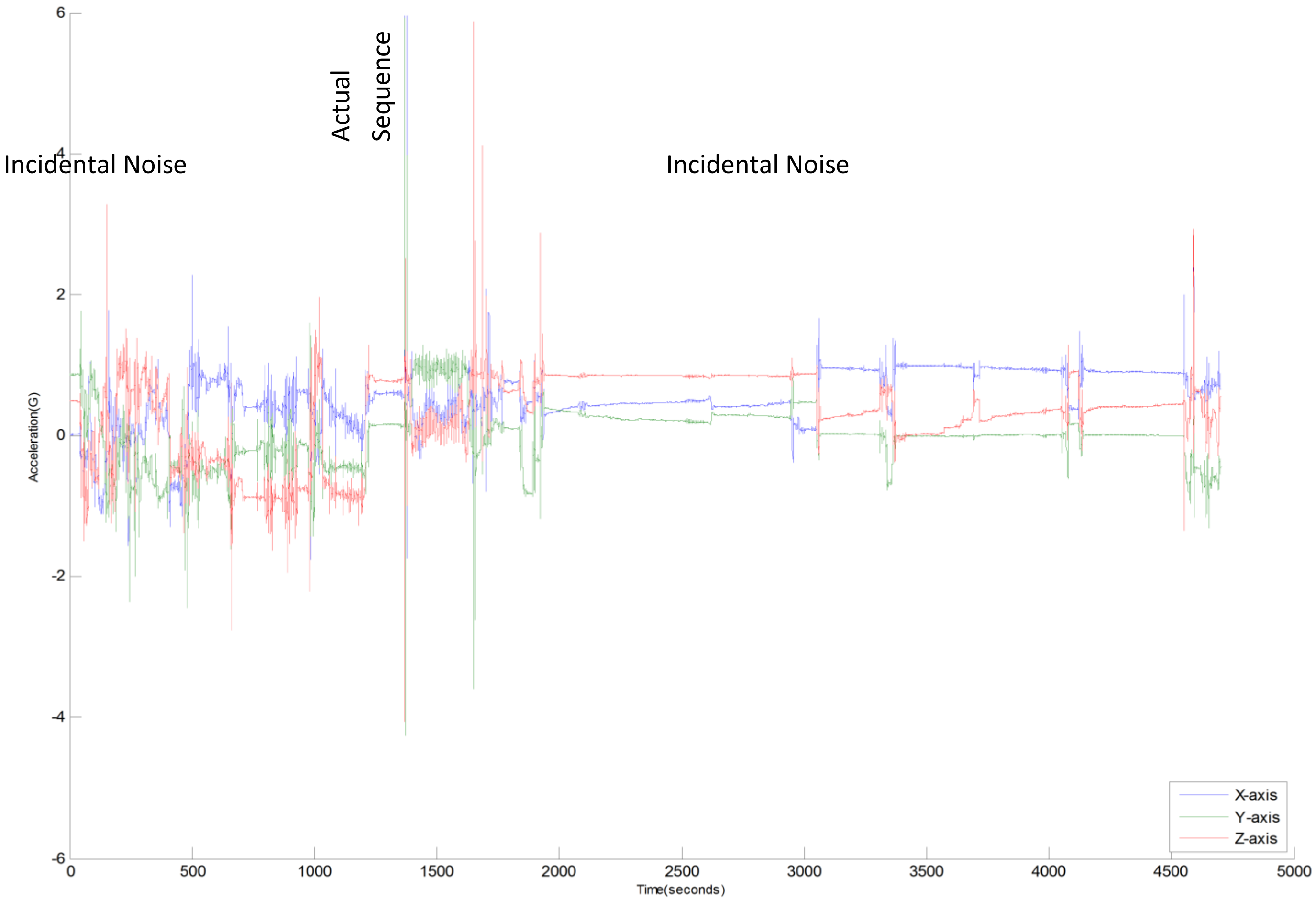

Figure 4.3 :Sample plot showing accelerometer whole recording with annotations of incidental noise and actual sequence.

Therefore, the thresholds are set as following:

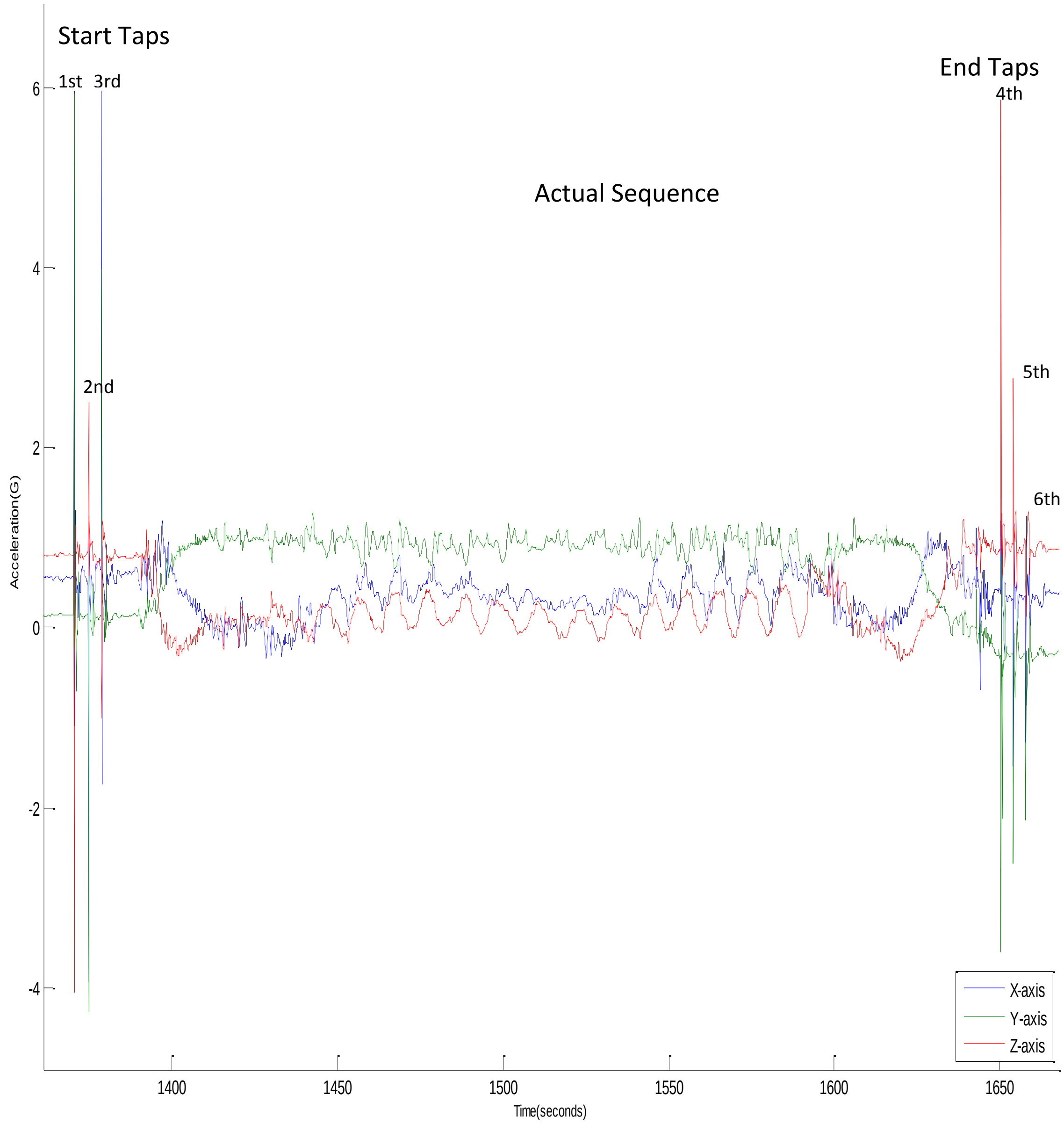

Figure 4.4 shows the movement sequence with taps numbered from 1 to 6. Where start taps are 1-3 and end taps are 4-6.

Thresholds for distance between the taps: To determine the thresholds for minimum and maximum values for the distances, 50 files were selected at random from all participants' files. The box plots of distance between the taps are shown in the Figure 4.5. The mean ± SD distances between any two consecutive taps are 0.47±0.11 seconds, with a maximum and minimum value of 1.02 seconds and 0.28 seconds, respectively. To accommodate any values in future approximately 30% tolerance was set for the minimum values which yields minimum threshold to be 0.2 seconds. Few times, first and last tap signatures were only made and missing the 2nd (5th) tap at the start (end). Therefore, the maximum distance determined should be doubled to accommodate such discrepancies; hence the maximum threshold set was 2.0 seconds to identify the taps.

Threshold for amplitude of the tap: To obtain the minimum threshold value for amplitude, sum of the square values of all the three axes of accelerometer recording are obtained. The taps signatures take negative values (see Figure 4.4); this does not allow determining a single threshold value. To overcome this issue, sum of the square (SS) values were determined, which makes the acceleration value unidirectional and moreover, makes the strength of taps signatures stronger for improved recognition.

$$SS = x^2 + y^2 + z^2 \tag{2.3}$$

Where**,** SS is sum of square value, x, y, z are the axes of accelerometer. At first, taps were identified using the amplitude thresholds and later the distance between the taps were verified using the flowchart shown in Figure 4.6.

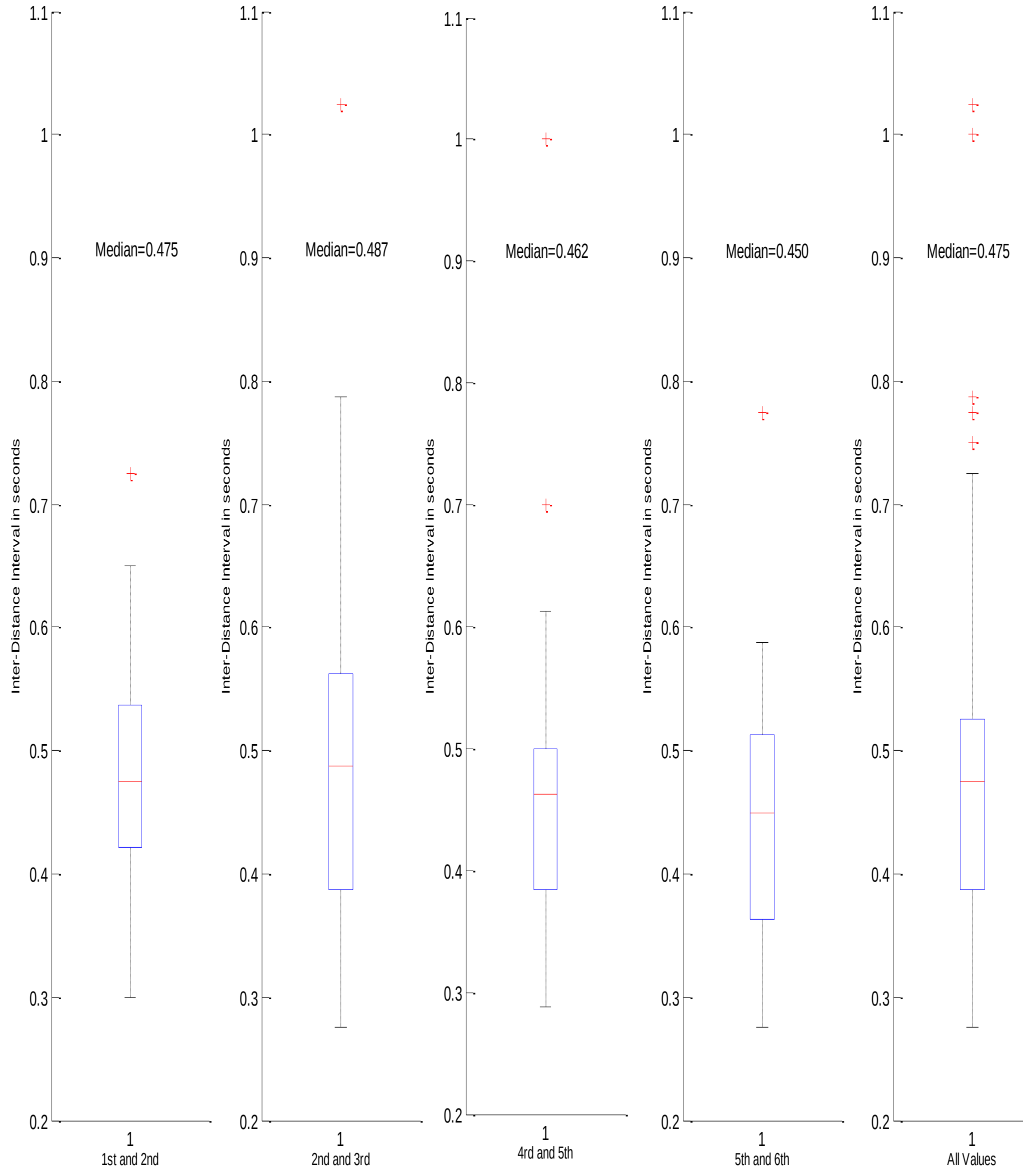

Figure 4.5 Box plot of inter distance interval (in seconds) between the first and last taps sequence obtained from the 50 participants samples measured manually. Refer to Figure 4.4 for the taps.

For some of the participants, taps were very weak in amplitude and could not be identified appropriately leading to false sequence identification. To overcome this, an additional algorithm was developed, which verifies all the extractions.

Initially a threshold value of19 $(ms^{-2})^2$ was set. In few participants' recordings, the taps were inadequately executed; hence threshold value set initially resulted in large number of false sequence identification. To overcome this, an additionally algorithm was developed. The most important factor for the false sequence identification is that the poor strength of taps. Hence amplitude thresholds were to be reduced subsequently followed by an iterative search in the neighbourhood for tap signatures at lower thresholds to find the weak taps. Verification algorithm of the extracted sequence is shown in Figure 4.6.

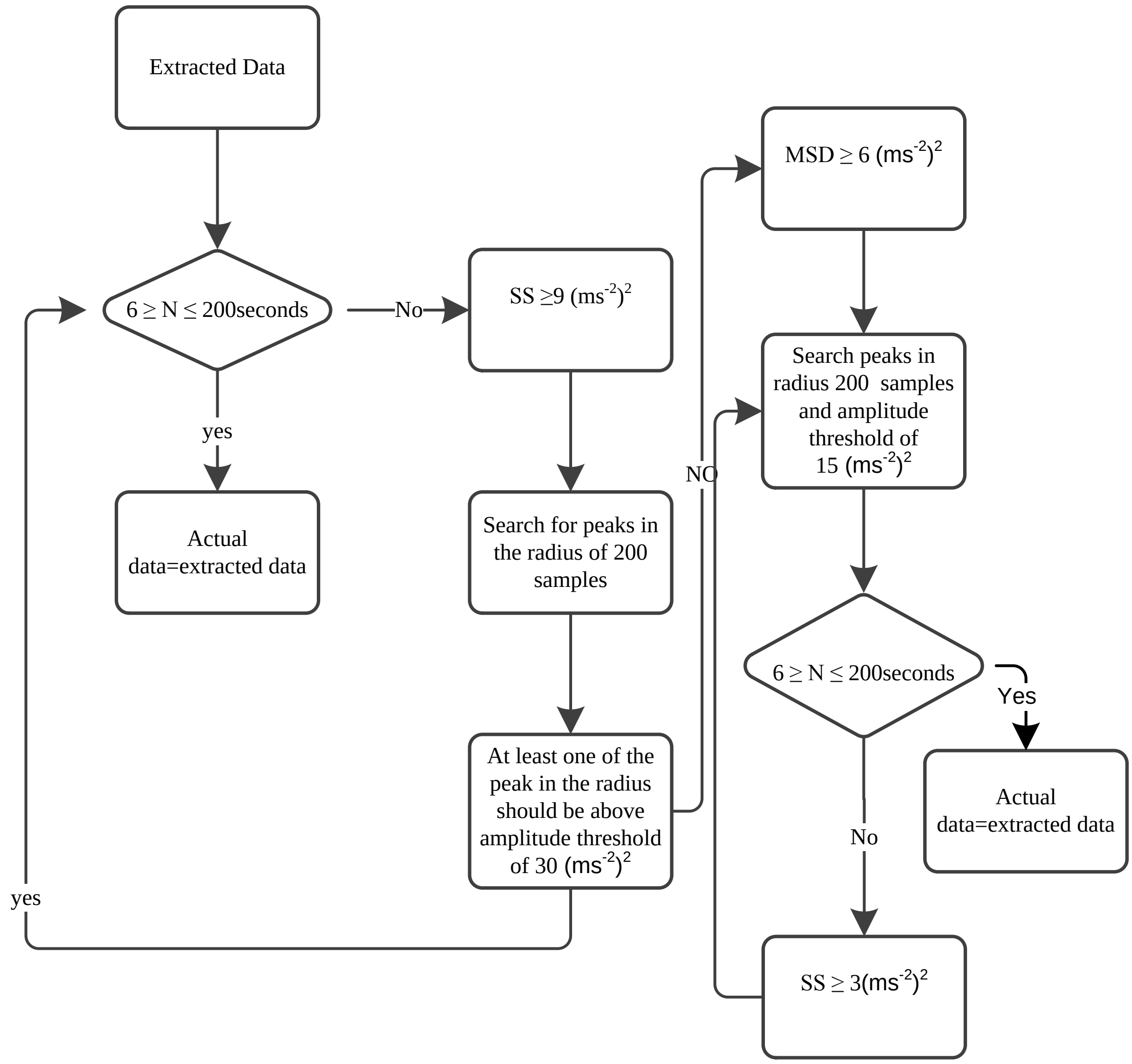

Figure 4.6 Flowchart showing the verification process for delineation of TUG movement sequence.

The movement sequence was identified with the taps. Hence, taps has to be removed prior to parameter extraction from the extracted sequence. The taps were removed by searching for the peaks greater than 50% of the M value shown in Eq.3.

$$SVM[n] = \sqrt{x^2 + y^2 + z^2} \tag{2.4}$$

$$Mean = \frac{\sum_{n=1}^{N_l} SVM[n]}{N_l} \tag{2.5}$$

$$M[n] = mean - SVM[n] \tag{2.6}$$

Where n is the sample number, the search was only made for first and last N_l = 50 samples of the signal where taps would be present. After the taps, there is an inevitable short delay before a movement; similarly, there was a further quiescent period between the completion of the TUG test sequence and the end taps. In order to remove this delay time, a Redmond *et al*. [121] algorithm was adapted to remove these quiescent periods adjacent to the TUG test movement sequence. Redmond *et al.* algorithm was adapted for the purposes of refinement only. The refinement algorithm is customized to search only 4.5s of data from the start taps and also from end taps for computational efficiency. From the refined sequence, the time for completion of test was found by dividing the number of samples by the sampling frequency (80 Hz), this time was called the algorithm extracted time (E-Time).

4.4. Placement of the device and features extracted

It is expected that the participants may not place the accelerometer in the strictly defined position. Therefore, attention is to be provided on types of features extracted. In a supervised environment, supervising staff would place the sensor on the correct position. When it is used in the unsupervised environment, there is no guarantee of strict accelerometer placement. Moreover, although the device is placed properly, there would be mild to moderate displacement of the accelerometer sensor during the test. This limits the type of features extracted.

If features are extracted without considering device's placement, features extracted would be meaningless. Also, location of the device placed limits the types of features extracted. For example: consider extracting the stride length of an individual, device placed in the shanks or feet would provide more faithful results than the one placed in the upper body.

4.5. Extracted Features

A number of features were extracted from the TUG movement sequence delineated algorithmically. Features were extracted from the each of the accelerometer axes x, y, z and SVM (refer equation 2.5 of Chapter 2) which may have characteristics to estimate fallers. The following section describes the pre-processing procedure undertaken and methodology by which features are extracted in detail.

4.5.1. Pre-processing

A high pass filter is implemented to reduce the contribution of gravitational components and to analyse signals related to body components (BA(t)). Signal that relates only to the body components were extracted using the filter previously discussed in the Section 3.7. BA(t) used in all the feature extraction.

The features extracted are broadly categorised into two categories

- Spectral features
- Energy/intensity features

4.5.1. Spectral features

4.5.1.1. Number of Frequency Band Changes/Switches (NOS)

Falls risk factors are described earlier in chapter 3, one of the notable intrinsic risk factors of falls is balance and stability. It is expected that fallers have reduced body control due to issues with balance and stability and these issues may have reflected in movements during TUG test.

The hypothesis is that due to reduced body movement control (inherent in their movement) while performing TUG test participant may tend to modulate frequencies. This modulation in frequencies may have an association with the falls. Fallers are likely to have lesser balance and control than the non-fallers. Therefore, higher frequency modulations are expected from fallers to non-fallers, relatively. To measure these modulations, novel feature called as 'Number of Frequency band changes/switches' (NOS) was extracted.

TUG test consists of simple sequential tasks which are usually performed by an individual during their daily activities of living. It is already discussed that magnitude of accelerations fall within the range of 20Hz in section 3.5 of chapter 3. Four frequency bands up to 20 Hz were defined to measure the modulations. Sun *et al*.**[105]** reported, most of the energy for the daily activities of living lies within 5 Hz. Therefore, we define the reference band as, $Band_0 \leq 5Hz$. Moreover, as 99% of the accelerometer magnitudes are contained within 15 Hz **[68]**. Frequency spectrum was further split up to 15Hz into two bands as, $5Hz < Band_1 \leq 10Hz$ and $10Hz < Band_2 \leq 15Hz$. Final level was defined as $Band_3 > 15Hz$ which aimed to capture the remaining frequencies.

In order to identify the frequency band at which the TUG task is performed for a given time period, a spectrogram (fs=80Hz, Hamming window with no overlap) is generated with a window size of 0.125s, formulated as follows:

$$STFT\{x(n)\} = X(m,k) = \sum_{n=0}^{N-1} x[n]w[n-m]e^{\frac{-2\pi nk}{N}} \tag{4.1}$$

Where, STFT is the Short Time Fourier Transform, $X[n]$ is the input signal, w is the window, m and k are the time and frequency parameters, respectively. The power within each frequency bands (within the time window of 0.0125s) is summed, separately. The band yielding the maximum power amongst the frequency bands was considered as the identifying frequency band for particular time interval of the signal. This methodology was applied successively throughout the signal. Frequency was considered to have switched or changed, if the band identified for a particular time segment did not belong to preceding frequency band. The total number of switches was summed up for the whole TUG signal and this number is called NOS.

The bands defined are purely exploratory in nature; the appropriate values of frequencies bands are to be further examined. Example plot shows frequency bands switching for fallers and non-fallers. Features extracted are shown in the Table 4.1

Table 4.1 Summary of NOS features extracted

Feature No	Feature Name
1	TUGT-NOS of x-axis
2	TUGT-NOS of y-axis
3	TUGT-NOS of z-axis
4	TUGT-NOS of SVM

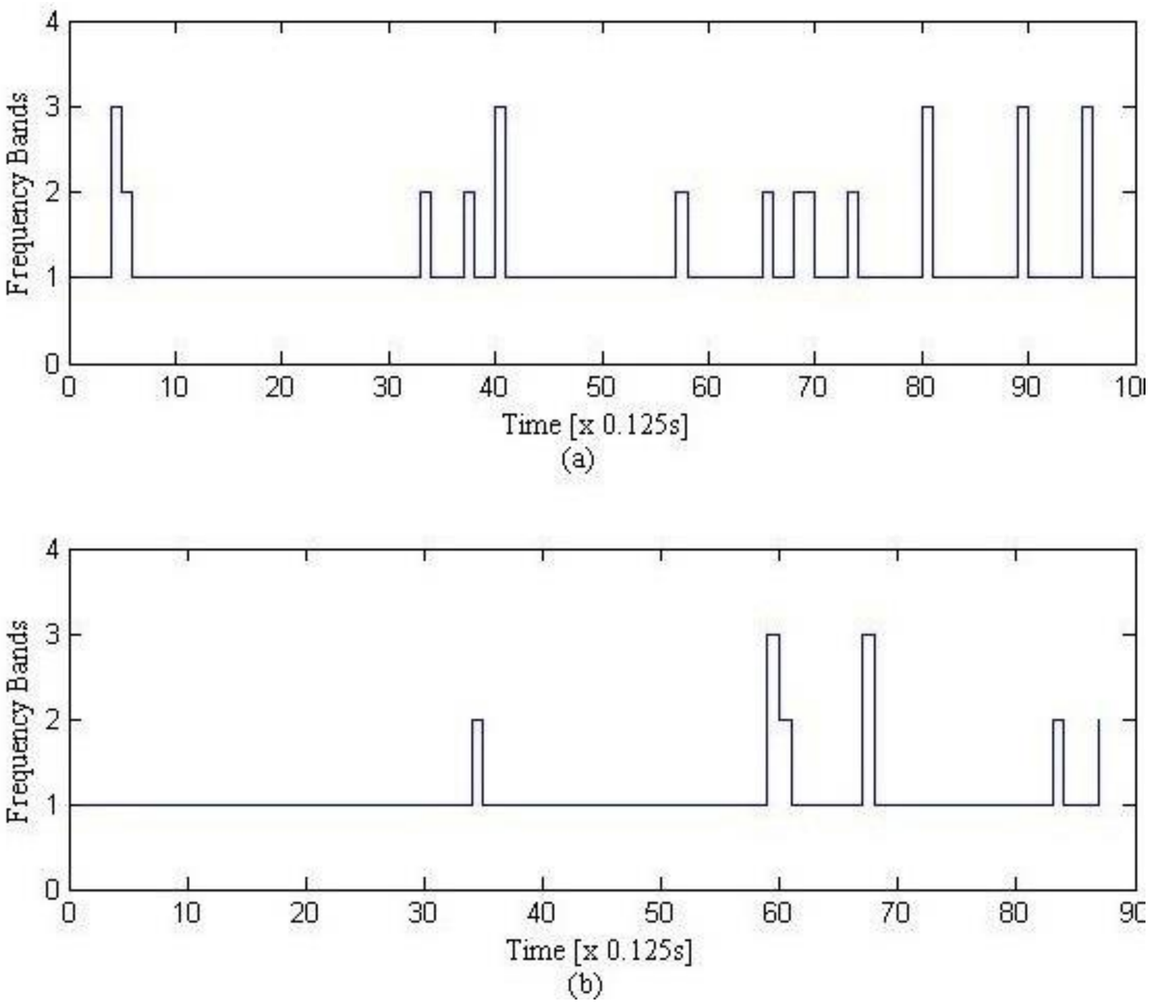

Figure 4.7 Comparison of NOS between (a) Fallers (manually timed TUG =10.19s), (b) Non-fallers (manually timed TUG =11.47s, freq. region =0.3-15Hz). Peaks in the plot show the identified frequency band for particular time interval (for example, in the top figure (a), frequency band is defined at level 1 until ~5s and then it shoots to level 3 and level 2, showing frequency band changes which may associate with instability issues), It can be seen that number of NOS in (a) is higher than (b) which implies that non-fallers tend to switch frequency lesser than fallers. Also, time to complete TUG protocol (manually timed TUG) for fallers and non-fallers are very similar whereas, NOS parameter has ability to distinguish them.

4.5.1.2. Sum of Magnitude of Power Spectrum

The ‘Sum of Magnitude of Power Spectrum’ (Smps) and sub features of it, showed power spread across the TUG frequency spectrum. It is hypothesized that non-fallers may perform the task more smoothly, whereas, fallers may tend to be exhibit greater variance due to loss of balance, fatigue and less controlled movements and exhibit flatter magnitude spectrum. To, investigate this, number of features from a discrete Fourier transform (FT) with a window size (l) of 1s and no overlap between successive windows are extracted. This is formulated as:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{\frac{-j2\pi nk}{N}} \tag{4.2}$$

$$powerspectrum[k_b; b] = \frac{1}{L} | X[k_b; L] |^2 \tag{4.3}$$

$$Smps = \frac{L}{N} \sum_{k=1}^{\frac{N}{L}} powerspectrum[k_b; b] \tag{4.4}$$

where, k is the frequency bin number , k = 0,1,....., $N-1$, N is the length of the signal, b is the block number, L is size of each block b defined by the window, K_b denotes frequency bin numbers within each bth block , K_b = 0,1..,$L-1$. Features numbers {5-8} shown in Table 4.2 refers to the mean Smps features extracted.

Many other sub features of Smps were extracted of the TUG signal in an attempt to characterize the TUG signal. Irregularity in TUG performance may reflect as the extreme values in Smps, and hence outliers were also extracted to investigate anomalies during the task.

Values of Smps greater than or equal to twice the value of the mean Smps are considered as outliers or anomalies. Features such as, mean of outlier Smps {13,..,16} , number of outliers {17,…,20} and mean Smps after exclusion of outliers {9,12} were all derived. In addition, to characterize the steadiness during the TUG task, features such as Standard Deviation (SD) of the difference in Smps value {21,…,24} and statistical measure Co-efficient Of Variation (COV), {25,…,28} which is the ratio of standard deviation to mean are extracted from the TUG signal. Graphical illustration of Smps features extraction is shown in Figure 4.9 for the list of intensity features extracted, refer to Table 4.2.

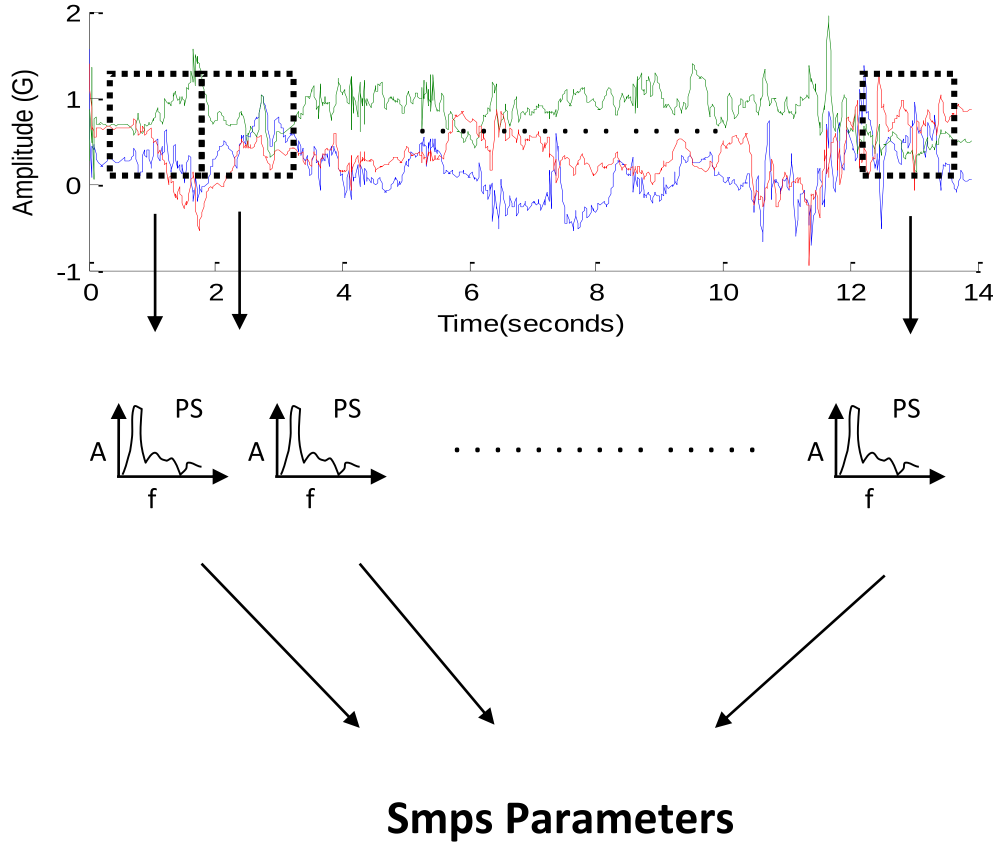

Figure 4.8 : Illustrates the methodology of Smps parameter extraction from TUG sequence extracted automatically using the developed protocol.

Table 4.2 Summary of SMPS features extracted

Feature No	Feature Name
5	Mean Smps of x-axis
6	Mean Smps of y-axis
7	Mean Smps of z-axis
8	Mean Smps of SVM
9	Outlier excluded mean Smps of x-axis
10	Outlier excluded mean Smps of y-axis
11	Outlier excluded mean Smps of z-axis
12	Outlier excluded mean Smps of SVM
13	Mean of the outlier Smps of x-axis
14	Mean of the outlier Smps of y-axis
15	Mean of the outlier Smps of z-axis
16	Mean of the outlier Smps of SVM-axis
17	Number of outliers Smps of x-axis
18	Number of outliers Smps of y-axis
19	Number of outliers Smps of z-axis
20	Number of outliers Smps of SVM-axis
21	SD of Smps difference of x-axis
22	SD of Smps difference of y-axis
23	SD of Smps difference of z-axis
24	SD of Smps difference of SVM
25	COV of Smps x-axis
26	COV of Smps y-axis

27	COV of Smps z-axis
28	COV of Smps SVM
29	SD of COV differences of x-axis
30	SD of COV differences of Y-axis
31	SD of COV differences of z-axis
32	SD of COV differences of SVM

4.5.1.3. Intensity Features

Intensity features are extracted to capture intensity spread across the TUG test signals of accelerometer. Intensity is a ratio of power to the area under the 1s signal. Sum of intensity is sum of all the intensity values under each window across the whole signal, given as feature numbers {5-8} in Table 4.3. Similarly, mean intensity is calculated and given as feature numbers {1-4}.

We hypothesized that instability and balance issues arise while performing TUG and therefore, the participants may exercise more intensity to overcome the issues. We expect, these values would be notably higher than the usual intensity and may not be present all the times during TUG, we define these values as the Outliers. The Outliers are defined as following:

$$Outliers(i) = Intensity(i) \leq 2meanIntensity \quad (4.2)$$

Where, i =1 to total number of intensity values for a TUG signal. Features such as number of outliers, {13-16} and outliers excluded mean {9-12} are extracted. For a normal performance, intensity value under each time window will be approximately equal showing the smoothness of the performance. But for participants with balance issues, intensity values may not be similar and vary throughout TUG test. Features such as intensity difference and sub features of it were extracted to quantify the changes in intensity. It is expected that, the difference would have direct relationship with the level of balance issues with the participants, in other words, more the difference, higher the problems with balance and stability.

Similarly to Smps, features such as, Standard Deviation (SD) of the difference in intensity values {25-28}, statistical measure the Co-efficient Of Variation (COV) which is the ratio of SD to mean are also calculated. SD and COV are extracted for intensity {29-32} and difference in intensity values {33-36}. The sum intensity features are calculated referred as feature numbers of {37-40}, respectively. All the features are extracted separately for each x, y, z axes of the signal and SVM. For all the list of intensity features extracted see Table 4.3.

Table 4.3 Summary of Intensity features extracted

Feature No	Feature Name
33	Mean Intensity of x-axis
34	Mean Intensity of y-axis
35	Mean Intensity of z-axis
36	Mean Intensity of SVM
37	Sum intensity of x-axis
38	Sum intensity of y-axis
39	Sum intensity of z-axis

40	Sum intensity of SVM
41	Outlier excluded mean Intensity of x-axis
42	Outlier excluded mean Intensity of y-axis
43	Outlier excluded mean Intensity of z-axis
44	Outlier excluded mean Intensity of SVM
45	Number of outliers Intensity of x-axis
46	Number of outliers Intensity of y-axis
47	Number of outliers Intensity of z-axis
48	Number of outliers Intensity of SVM-axis
49	Power of x-axis
50	Power of y-axis
51	Power of z-axis
52	Power of SVM axis
53	Area of x-axis
54	Area of y-axis
55	Area of z-axis
56	Area of SVM axis
57	SD of intensity difference x-axis
58	SD of intensity difference y-axis
59	SD of intensity difference z-axis
60	SD of intensity difference SVM
61	COV of intensity x-axis
62	COV of intensity y-axis

63	COV of intensity z-axis
64	COV of intensity SVM
65	SD of COV intensity differences of x-axis
66	SD of COV intensity differences of Y-axis
67	SD of COV intensity differences of z-axis
68	SD of COV intensity differences of SVM

Considering the sensor placement at the wrist location, features from other studies that may be meaningful were also extracted in order to compare the ability of features extracted in this study estimating falls. Other features extracted in the study are shown in Table 4.4.

Table 4.4 Others features used in the study

Feature No	Feature Name
69	TUGT first 6 harm. Freq. ratio of x-axis
70	TUGT first 6 harm. Freq. ratio of y-axis
71	TUGT first 6 harm. Freq. ratio of z-axis
72	TUGT first 6 harm. Freq. ratio of SVM
73	TUGT Fund. harm. magnitude ratio of x-axis
74	TUGT Fund. harm. magnitude ratio of y-axis
75	TUGT Fund. harm. magnitude ratio of z-axis
76	TUGT Fund. harm. magnitude ratio of SVM
77	TUGT 2nd. harm. magnitude ratio of x-axis

78	TUGT 2nd. harm. magnitude ratio of y-axis
79	TUGT 2nd. harm. magnitude ratio of z-axis
80	TUGT 2nd. harm. magnitude ratio of SVM
81	TUGT 3rd. harm. magnitude ratio of x-axis
82	TUGT 3rd. harm. magnitude ratio of y-axis
83	TUGT 3rd. harm. magnitude ratio of z-axis
84	TUGT 3rd. harm. magnitude ratio of SVM
85	TUGT 4th. harm. magnitude ratio of x-axis
86	TUGT 4th. harm. magnitude ratio of y-axis
87	TUGT 4th. harm. magnitude ratio of z-axis
88	TUGT 4th. harm. magnitude ratio of SVM
89	TUGT even to odd harm. magnitude ratio of x-axis
90	TUGT even to odd harm. magnitude ratio of y-axis
91	TUGT even to odd harm. magnitude ratio of z-axis
92	TUGT even to odd harm. magnitude ratio of SVM
93	TUGT RMS SVM
94	TUGT SMA mean
95	TUGT SMA Variance

Features numbers 69-92 are adapted from Liu *et al.[89]*

4.6. Feature Selection and Classification

In total 95 features (24 features from other study) were extracted in this study. A large number of features extracted show the need for feature selection. Feature selection allows reducing the number of features by discarding features that are irrelevant, redundant and improves the learning ability of the classification algorithms. The benefits of feature selection are:

1. Allows, more comprehensibility of results, less features allows interpreting the results better and easier.
2. Limits or avoids over fitting of the model, models built with large number of features are subjective to the data under the study and tend to over fit the new data.
3. Reduces the issues with dimensions, if the number of features increases, then the dimensions of the data under study for fair result increases.
4. Takes less time to process and improves performance of the machine learning algorithms.
5. Dimensional reduction techniques such as Principal Component Analysis (PCA), transform the features into reduced new feature variables, hence the actual feature extracted is lost. Whereas, in feature selection the actual feature extracted are preserved and offers more insight into the clinically interpretability of the extracted features.

In this study novel hybrid feature selection algorithm implemented the following section presents feature selection methodology implemented in the study.

The first step in the feature selection is the Mann-Whitney non–parametric test [4], this step significantly reduces the processing time of the feature selection algorithm implemented.

Mann-Whitney test does not assume the data is normally distributed. Mann-Whitney non-parametric tests the data in a feature under the null hypothesis that it is same for all the participants, against the alternative hypothesis that they are not. Discriminative features are features that show ability to discriminative between fallers and non-fallers. Discriminative ability is determined by the significance level (p-value) yielded by the test for a feature. In our analysis, p-value of 0.05 was set, features that show p-value[6] less than 0.05 were considered as discriminative features (DF).

4.6.1. Cross-Validation

Cross-validation is a validation technique of the developed model in order to identify the significance of the results in practice or in other words for an unbiased estimate of the performance of the model [3]. Validation involves in splitting the data samples into testing and training data set. Training data samples are used to train the model and testing data samples are unseen by the model (during the training) and are used to evaluate the trained model. Cross-validation involves holding the different data sample for training and testing data set every time, reducing the variability in performance estimates. The common types of cross-validation are

1. Hold out method or 2-fold cross validation

[6] Probability value (p-value) is the estimated probability of rejecting the null hypothesis when the study hypothesis is true.

2. K-fold cross validation

3. Leave-one-out cross-validation

All the cross-validation methods [8] could be commonly called as K-fold cross-validation, in which if k equals 2, it means that available data samples are split equally into training and testing data set. If we assign variable names to the split, DS1 and DS2, 2-fold cross validation involves at first, training the model with DS1 and testing it with DS2 and then training it with DS2 and testing it with DS1. In K-fold cross-validation, available data samples are split into K equal subsample set and one of the subsample set is held as the testing data sample, others as training data sample. This process is repeated K-times, withholding different testing data sample each time. Leave-One-Out cross validation (LOOCV) is the special case of K-fold cross validation where K equals number of data samples.

LOOCV involves in withholding one of the participants' data and training the model with the remaining. The withheld data known as test data is later estimated using the trained model. This process is repeated N_t times, where N_t is the total number of participants in a group, each time withholding different test data as shown in Figure 4.10 Leave-One-Out cross validation (LOOCV) is utilised in the work to obtain unbiased evaluation of the model performance.

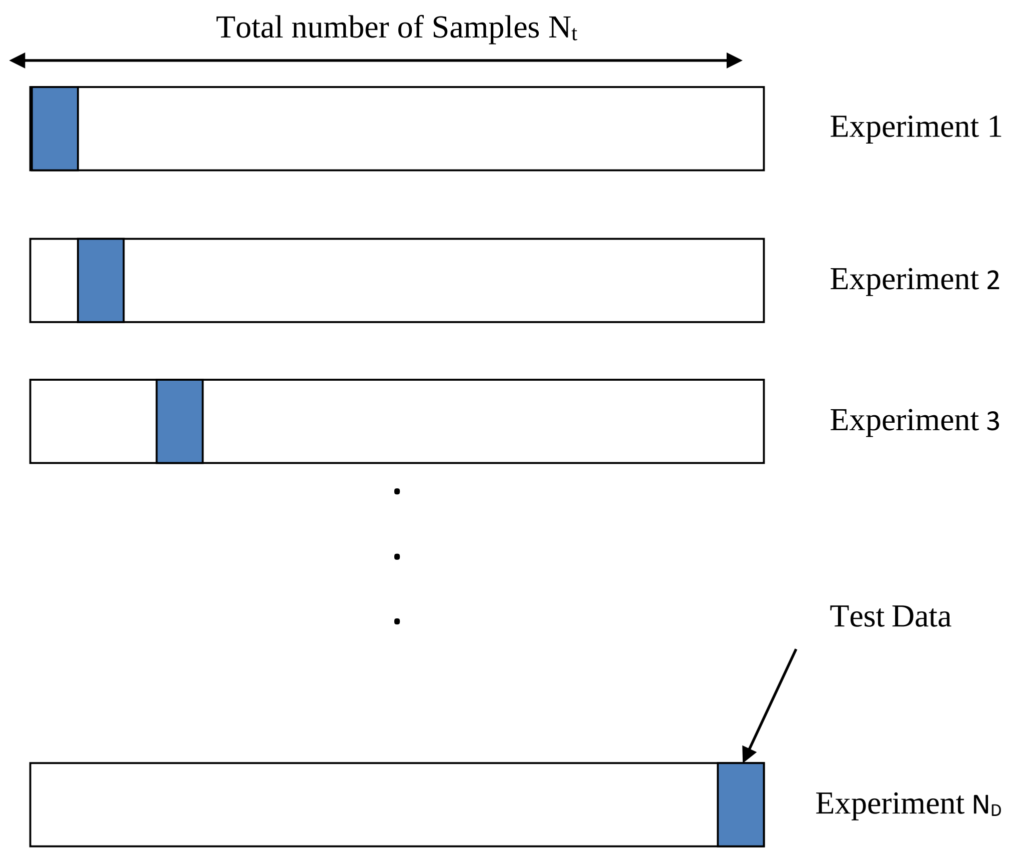

Figure 4.9 Illustrates, Leave one-out cross validation procedure.

For an unbiased estimate of the model's performance and generalized performance of the model, robust feature selection is required. In this thesis, nested LOOCV is used for this purpose. For selection of features that are reliable, exhaustive search using the scatter matrices as a criterion is utilised.

The feature selection aims the following:

1. To maximize the distance between the features
2. To minimize the distance within the features,

For this purpose, this report uses scatter matrices with the criterion J .

$$Sw = \sum_{i=1}^{C} P_i S_i \tag{4.3}$$

$$S_b = \sum_{i=1}^{C} P_i (m_i - m_0)(m_i - m_0)^T \tag{4.4}$$

$$J = trace\{S_w^{-1} S_b\} \tag{4.5}$$

Where P_i is the prior probability of the class from $i = 1,2,..c$ and S_i co-variance matrix of the class i and $m_0 = \sum_{i=1}^{c} P_i m_i$. Larger the J value shows that data in a feature are close to each other and at distant from other class.

In this thesis, optimal search method exhaustive search was used. In this method all the possibility of the feature combinations selected are exhaustively formed and class separability measure criterion J was computed.

4.6.2. Summary of methodology followed in features Selection and evaluation

In total 95 parameters are extracted from the accelerometer, the methodology of parameter selection is shown in the Figure 4.10. Parameter selection involves in five steps,

i) Identifying parameters that has an ability to discriminate the fallers and non-fallers (Mann-Whitney non-parametric test)

ii) Identified discriminative parameters (parameters that have ability to discriminate) were cross-validated (LOOCV1) into training and test sets

iii) For each of 1 to N_D, utilizing the train set of LOOCV1, exhaustive search is performed to identify the best parameter combinations. Different training sets yield different subset of parameters, therefore, most repeated subset was selected as the best subset for the selected number of combinations

iv) The train set of LOOCV1 was again cross-validated into LOOCV2, where train set of LOOCV2 was utilized for training the logistic regression classifier and was evaluated using the test set of LOOCV2

v) Final best parameter subset were found as the subset which yields best accuracy (as evaluated on LOOCV2 test set) and these selected parameters were finally validated using the LOOCV1 test set.

Figure 4.10. Illustrates the parameter selection procedure and evaluation.

4.1. Conclusion

The methodology for extracting the movement sequence from the whole recording is presented. Simple threshold based algorithm is developed which identifies the taps signatures at the start and end of the movement sequence. 95 features are extracted from the TUG signal and due to large number of features extracted feature selection is necessary. Feature selection permits identifying the features of importance that have an ability to discriminate fallers from non-fallers. Hybrid feature selection algorithm is implemented where the initial screening of features of importance is done using Mann-Whitney U test. The identified features are given as an input to the exhaustive search algorithm which searches for the best combination of parameters as validated by nested LOOCV.

The next chapter presents the performance of the delineation algorithm developed. Followed by performance results of accelerometer model developed using the 95 features described in this chapter.

Chapter 5

5. Results and Discussions

5.1. Introduction

This chapter firstly presents the demographics of the participants participated in the study. Secondly, presents the performance of algorithm developed to extract the genuine movement sequence from whole accelerometer recordings. Subsequently, describing the correlation metrics between the extracted features, reference feature/M-time and the falls. Thirdly, it expresses the performance of the model developed with the optimal features selected using feature selection algorithm and compares it with the standard model developed using the reference feature, time taken to complete the test (M-time). Finally, it presents the ability of extracted features and feature selection algorithm to classify disability levels of the community dwelling individuals.

All the 484 participants of the NE85+ phase III study were utilised in the study. Of the total 484 participants, 80 participants did not attempt TUG test, one was not able to complete the test, two participants' data were found missing, six accelerometer files were corrupted and unreadable and one of the participant data about the use of walking aid was missing. These 90 files are excluded from the analysis. Therefore, a total of 394 (484-90) participants were included in the analysis. Of the 394 participants 42% (166/394) participants reported to have fallen at least once in the past 12 months. Demographics of the participants utilised in the study is given in Table 5.1.

Table 5.1 The Demographics of Participants of the Study

Walking Aid	N	Fallers		Non-fallers	
		Male	**Female**	**Male**	**Female**
Yes	73	16	27	8	22
No	321	53	70	84	114

Algorithm described in the chapter 4 to delineate the TUG movement sequence was implemented for all the participants' recordings in the current study.

Automated processing of the tri-axial TUG recordings requires careful attention to the design and execution of the TUG test protocol. The existing automated protocol places limitations on the protocol requiring careful delineation of the TUG test through the use of consecutive and consistent taps at an adequate intensity to isolate from incidental noise. Out of 394 files, 95 files did not fully adhere to the protocol, requiring manual segmentation before parameter extraction. The following are major reasons which did not allow the automated delineation of TUG movement sequence.

i) Taps were not found at start or end of the TUG movement recording.

ii) Only one tap was made at start or end or both of the TUG test.

iii) No taps were made before and after the TUG test.

However, successful automatic segmentation of 299 files (~76%) and consequent isolation of the TUG movement sequence demonstrates the feasibility of automated processing in the majority of the participants files.

For 95 participants' TUG movement sequences could not be extracted automatically and hence the movement sequence is delineated manually.

Comparison of delineated sequence with the reference feature: M-time (Manually extracted time) enables measuring the performance of the developed delineation algorithm. To compare the delineated sequence with the M-time, time taken from the extracted sequence is calculated as shown in equation 5.1.

$$Time\ Taken = \frac{Number\ of\ sample\ recorded\ in\ a\ TUG\ recording}{Sampling\ Frequency} \quad (5.1)$$

Two different time measures were extracted from the participants' recordings of the study,

i) Time taken measured from the 299 participants recordings who adhered to the delineation protocol using the developed delineation algorithm, referred as 'algorithm extracted time' (E-time)

ii) For the remaining 95 (394-299) participant's files with altered protocol, the TUG movement sequences are segmented manually through visual verification and time taken to complete the TUG test is referred as 'visually segmented time'.

Participants using walking aid were analysed separately, as utilisation of aid may have an effect in the movements which would have affected the accelerometer recording. This is confirmed by using the Mann-Whitney U test of the reference feature between participants who used walking aid and those that did not across gender. The results of test show statistical significant difference across the groups (with walking aid and without walking aid) with p-values of 1.76×10^{-11} and 2.39×10^{-19} for males and females, respectively. Thus all the analyses in this thesis report are performed separately across the groups.

Within the group, Mann-Whitney test is performed to study whether there were significant differences in time taken to complete the test between males and female. For the group not using walking aid, p-values appeared as 0.002 and 0.007 for M-time and E-time respectively, showing the significant difference. For WA group p-values appeared as 0.105 and 0.185 respectively for M-time and E-time respectively and show no difference between male and female. The Table 5.2 shows demographics of time for fallers and non-fallers, stratified based on gender and group for all 394 participants.

From Table 5.2, it is clear that the E-time extracted from the TUG movement sequence shows a mean and standard deviation values very close to the reference (nurse recorded time) M-time for both the groups. This shows that the developed algorithm for automatic delineation of the movement sequence is successful.

In addition, bland-Altman plot was plotted to compare the E-time with the reference M-time. Bland- Altman plot [9, 122] was widely used to compare the two methods or techniques. It compares a newly developed method with the gold standard method or reference method, allows determining how much does the old method differ from the new method and also whether an old method can be replaced with the new method.

Bland-Altman plot (Figure 5.1) compares the reference time (M-time) with the algorithm extracted time (E-time). It could be seen from Figure 5.1 that majority of the values are within the limits of agreement (+1.96SD to -1.96SD), indicating that almost 95% of values are in agreement. This again validates that the developed algorithm that delineates TUG sequence from whole recording is successful and can be readily implemented.

$Error$ was defined as the reference time minus the measured time.

$$Error = Mtime - Etime \tag{5.2}$$

The maximum difference between M-time and E-time was found to be -10.72 s, mean error is -0.9333s with the standard deviation is 1.91s.

TABLE 5.2 : Mean and Standard Deviation (SD) Values of Algorithm Extracted Time (E-Time), Visually Segmented Time and Manually Timed TUG (M-time) for Fallers and Non-Fallers Based on Gender. All the Values in the Table are in seconds.

Without Walking Aid

Variable	Fallers (mean±SD)		Non-fallers(mean±SD)	
	Male	*Female*	*Male*	*Female*
M-time (N=321)	16.71±7.38	19.5±11.61	14.13±4.74	16.52±6.72
E-time (N=258)	17.47±7.44	19.47±7.57	14.76±4.30	16.53±4.67
Visually segmented time (N=63)	21.28±7.19	24.49±13.6	20.27±5.27	22.48±10.82

With Walking Aid

Variable	Fallers (mean±SD)		Non-fallers (mean±SD)	
	Male	*Female*	*Male*	*Female*
M-time (N=73)	47.29±39.21	46.49±27.61	28.06±4.09	43.61±38.28
E-time (N=41)	32.97±13.59	37.20±19.88	27.74±3.45	33.66±11.54
Visually segmented time (N=32)	59.60±52.00	56.49±31.84	29.02±7.44	57.99±57.03

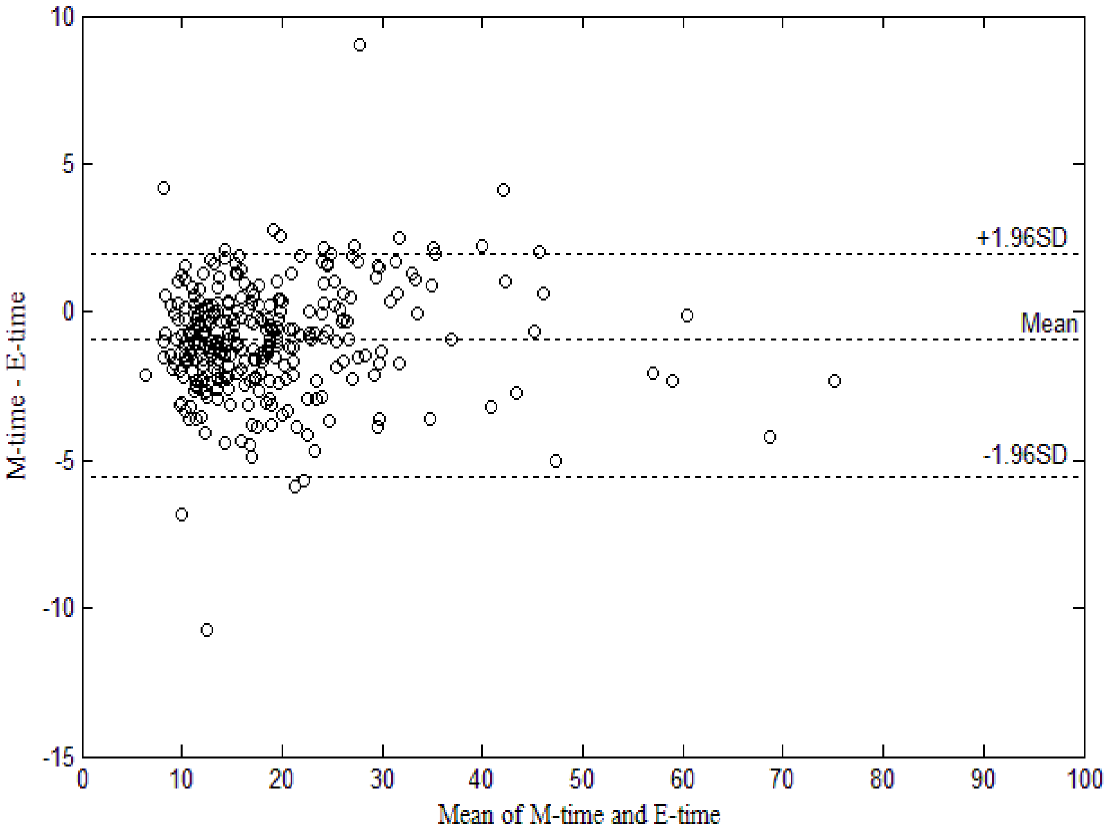

Figure 5.1 : Bland-Altman plot for the E-time and M-time. Most of the points are within the limits of agreement (+1.96SD to -1.96SD) lines indicating that M-time can be replaced with E-time.

In general females have taken longer time than male to complete the TUG test. It can be also seen that the visually segmented time is larger than any other times, this shows that the participants were frail and could not adhere to the protocol correctly.

5.2. Feature selection and Modelling

Table 5.3 shows the features that have the ability to discriminate fallers and non-fallers. It also shows the best combination of features selected obtained using the feature selection methodology described in the section 4.5 of Chapter 4. The best combinations of features are selected based on the highest accuracy as evaluated by the training set. The accuracy of various feature combinations is also shown in Figure 5.2. The feature combination which gives highest accuracy is circled.

It can be seen from the Table 5.3 that out of 95 features extracted from the accelerometer signals, only 13, 20 features for male and female participants' commonly show ability to discriminate fallers and non-fallers for the group With out Aid (evaluated by Mann-Whitney test). For the group with aid, only 2 features for male and 6 features for female showed significant difference between fallers and non-fallers.

It is interesting to see that reference measure M-time is only significant (discriminating fallers and non-fallers) for the female participants of the WoA group and non-significant otherwise. On contrast at least two of the features extracted from accelerometer shows discriminating ability and this demonstrates accelerometer features significance over M-time. Graphical illustrations of discriminative ability of features are shown as the box plots in Figure 5.4 and Figure 5.3.

Table 5.3: Features that have the ability to discriminate between fallers and non-fallers using the Mann-Whitney test. (2nd column). The best selected combination of parameters (3rd column) and significance of reference measure (m-time) in the last column.

Without walking aid(WoA)			
Gender	**Mann-Whitney test**	**Best combination**	**M-time**
Male	{5,8,9,10,11,12,15,30,32,43,93-95}	{8,9,10,11,32,93-95}	Not Significant
Female	{2,3,8,9,10,12,14,17,18,20 ,40,43,45,46,48,50,54,91,93}	{2,3,8,9,10,14,20,45,48,50,91}	Significant

With walking aid			
Gender	**Mann-Whitney test**	**Best combination**	**M-time**
Male	{39,60}	{20,34}	Not significant
Female	{26,30,48,60,78,90}	{26,30,60,78}	Not significant

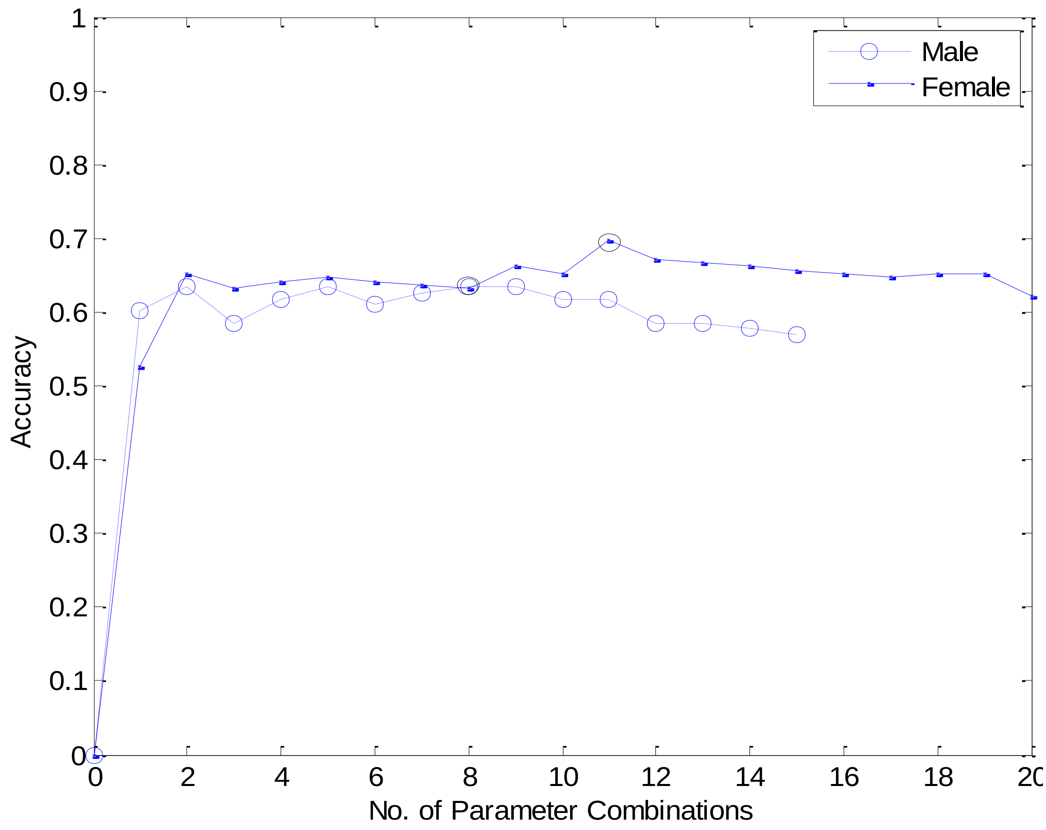

Figure 5.2 Various feature combinations with accuracy of classification fallers and non-fallers for a train set as evaluated by LOOCV, features combinations that gives highest accuracy is circled.

From Figure 5.3 and Figure 5.4 it can be seen that the mean Smps and other features of Smps show relatively lower value for fallers than non- fallers. As hypothesized, non-fallers do not perform the task smoothly; hence a flatter magnitude spectrum (white noise has flat magnitude spectra) is obtained which is reflected in the Smps features values. In addition, as expected the SD of COV difference is found higher for fallers showing the inconsistency/variability during the TUG test compared to non-fallers.

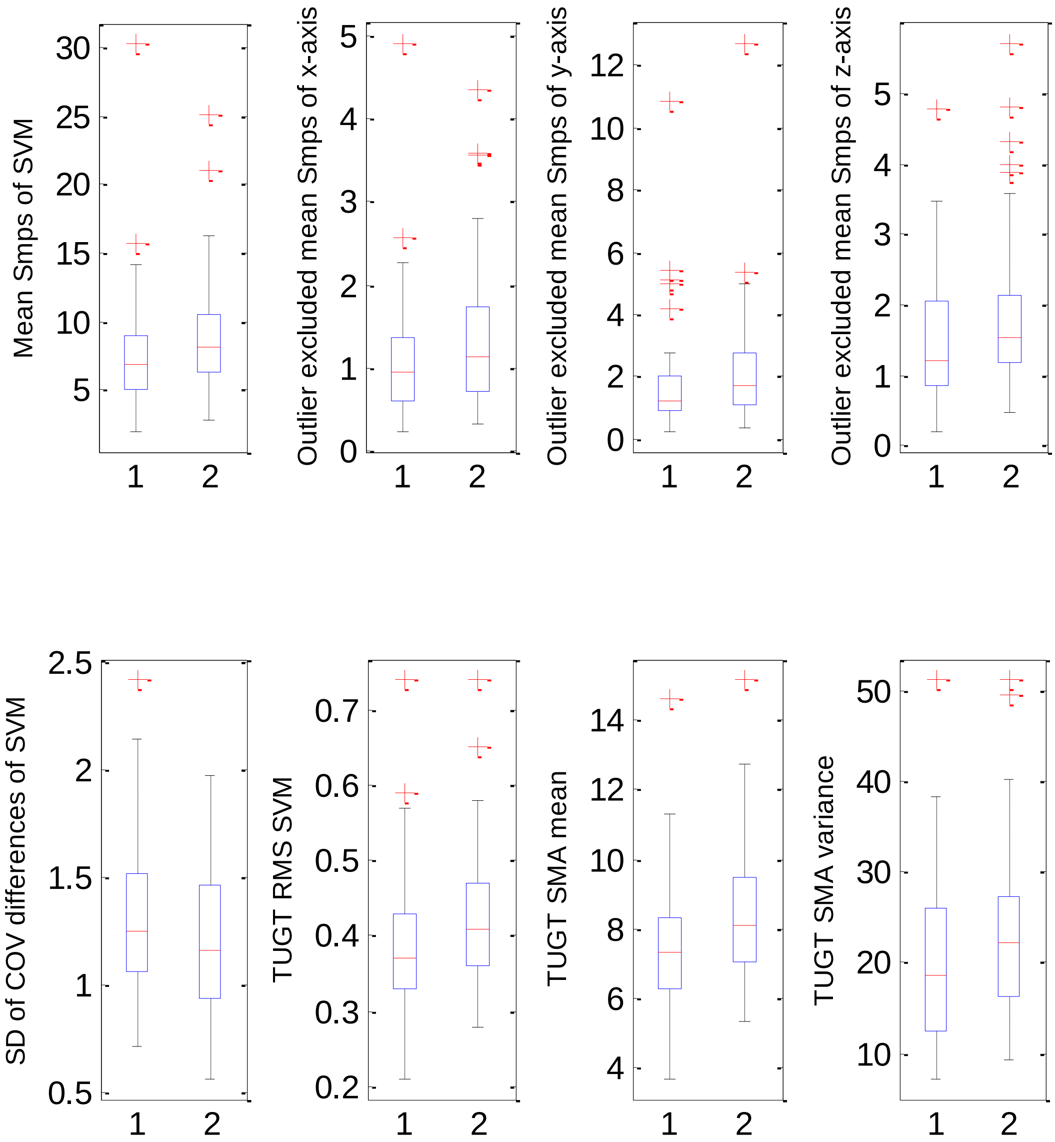

Figure 5.3: Boxplot showing the discriminating ability of features that are selected as best combination for male participants of the group WoA. 1-fallers , 2-Non-fallers.

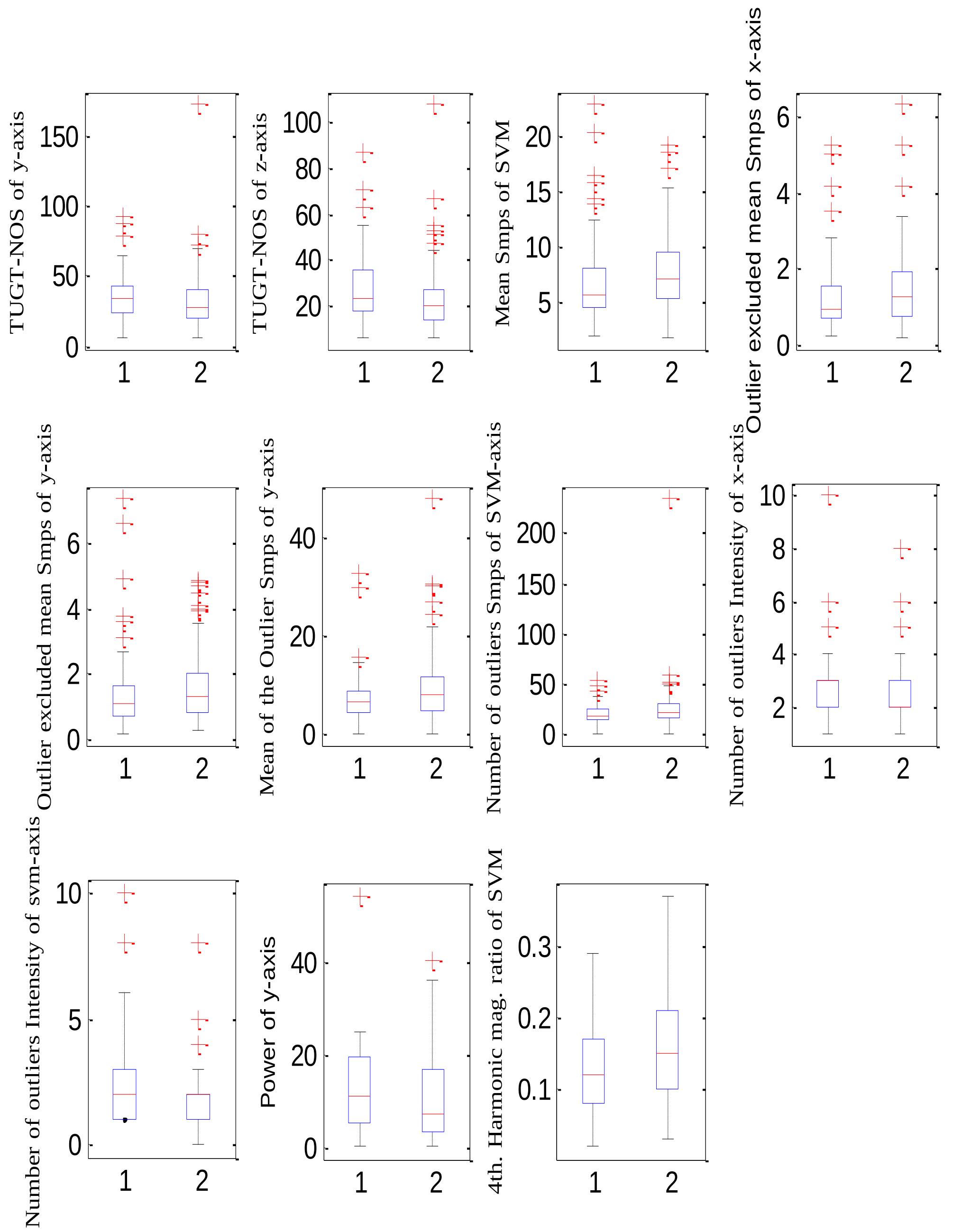

Figure 5.4: Boxplot showing the discriminating ability of features that are selected as best combination for female participants of the group WoA. 1-fallers, 2-Non-fallers.

The SMA has been shown to estimate the metabolic energy expenditure [119] [118, 123]. It is reported in that [124] that higher energy expenditure less prone to falling. The box plot of SMA and the features SMA, RMS of this study show that non-fallers expend more energy than non-fallers, which again validates the hypothesis.

The Box plot shows higher NOS for fallers than non-fallers which validates the hypothesis that more the NOS more prone to falling. As explained earlier in the Chapter 4, NOS captures the instability issues during TUG test, hence more the NOS more prone to falls.

5.2.1. Performance of the model developed

Considering the investigative nature of the study, a simple logistic regression classifier was used in this work to comprehend the ability of extracted features predicting falls. The theory of regression analysis is described in the section 2.7.5.2 of Chapter 2. Models using logistic regression classifier were built for male and female, separately.

To evaluate the developed models' performance metrics such as sensitivity, specificity, accuracy and Receiver Operating Characteristics (ROC) curve were the developed models. Sensitivity is defined as the proportion of fallers identified as the fallers. Specificity is defined as Proportion of non-fallers correctly identified as the non-fallers. Accuracy is defined as the overall correct classification of fallers and non-fallers by the developed model.

$$Specificity(\%) = \frac{TN}{TN + FP} \quad (5.3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \quad (5.4)$$

$$Sensitivity(\%) = \frac{TP}{TP + FN} \quad (5.5)$$

Where,

TP-True Positives: Numbers of fallers classified as the fallers

FP-False Positives: Number of non-fallers classified as the fallers.

TN-True Negative: Number of non-fallers classified as non-fallers.

FN-False Negative: Number of fallers classified as non-fallers.

ROC curves illustrate the performance of the models developed graphically. In addition, Area under of the curve (AUC) is also calculated from ROC curve. AUC shows the statistical performance of the models developed and it is comparable to the Mann-Whitney U test of the two samples non parametric Wilcoxon rank sum test [22]. Table 5.4 shows the performance metrics of the logistic regression models developed for male and female participants and for the groups.

Table 5.4 Compares the logistic regression developed using the best features combined and M-time. The results shown are models performance on evaluation of test set.

Without Walking Aid

	Sensitivity		**Specificity**		**Accuracy**		**AUC**	
	E-score	M-Time	E-score	M-Time	E-score	M-Time	E-score	M-Time
Male	47.17%	22.64%	75.71%	81.42%	63.41%	56.09%	0.63	0.54
Female	59.52%	16.60%	77.19%	87.70%	69.69%	57.57%	0.71	0.57
Mean	53.35%	19.62%	76.45%	84.56%	66.55%	56.83%	0.67	0.55

With Walking Aid

	Sensitivity		**Specificity**		**Accuracy**		**AUC**	
	E-score	M-Time	E-score	M-Time	E-score	M-Time	E-score	M-Time
Male	75.00%	75.00%	37.50%	12.50%	62.50%	54.16%	0.50	0.60
Female	74.07%	70.37%	63.63%	23.80%	69.39%	50.00%	0.72	0.48
Mean	74.54%	72.69%	50.57%	18.15%	65.94%	52.08%	0.61	0.54

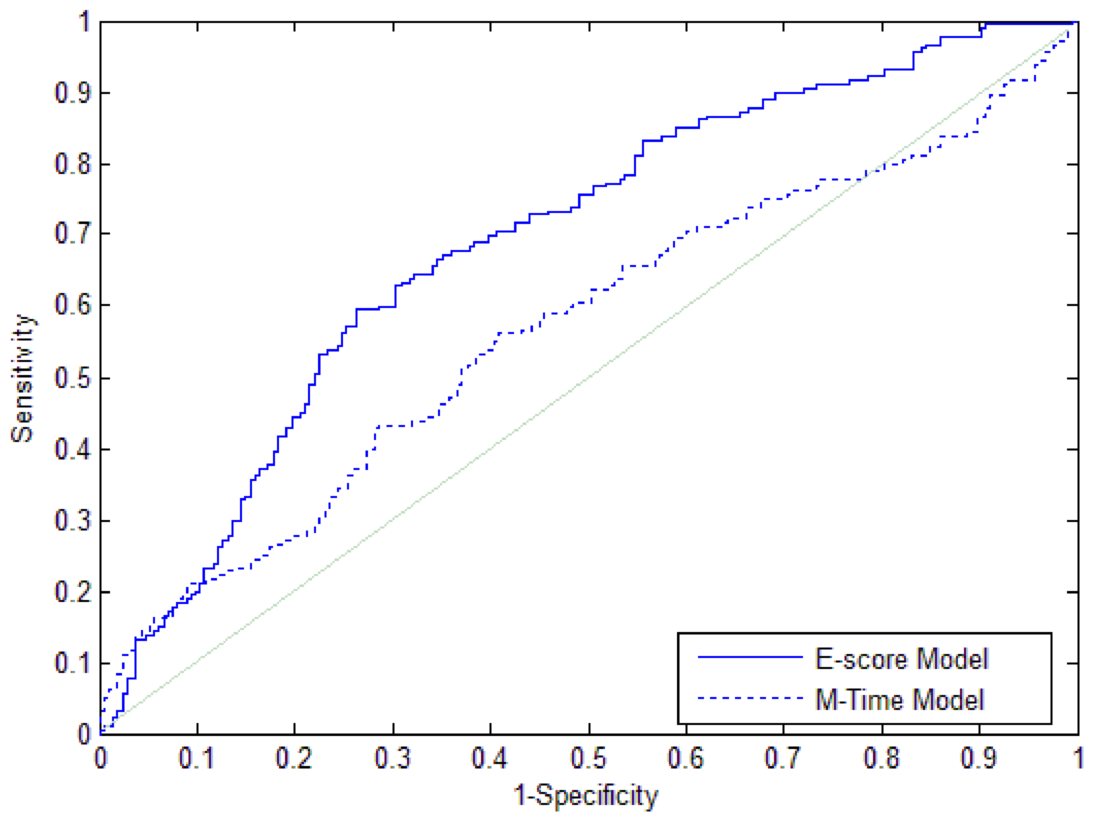

Figure 5.5 Compares the ROC of M-time model and E-score model combined ROC for both the gender and groups

5.1. Comparison of results with cut-off values determined from other studies

In order to examine the value of the developed models estimating prior falls risk; best performance metrics of the E-score model and M-time model were compared. Best performance metrics are described based on cut-off value consideration which depends upon the application.

Alexandre *et al.[125]* investigated ability of the TUG test (only time taken to complete) identifying fallers of the data collected from 60 community dwelling individuals and compared the results to [47],[124]. Results of [125] reported to outperform others studies [47],[124].

Therefore, to understand the value of the current study undertaken, the cut-off value described in [125] was utilized to compare M-time and E-score models. Figure 5.5 compares the M-time and E-score performance for the cut-offs determined by [125] and also best cut-off (where the sensitivity and specificity curve intersects) determined by the M-time. (Refer Table 5.5).

Table 5.5 Comparison of accelerometer models performance against M-time and past literature [125] for both genders who did not use walking aid

Cut-Off	**M-Time**		**E-score**	
	Sensitivity	**Specificity**	**Sensitivity**	**Specificity**
[125]	68.58%	32.09%	68.13%	53.50%
Best cut off determined by M-time of the study	54.99%	54.99%	67.19%	59.43%

The values shown in the Table 5.5 are only for the group, without walking aid for both genders. This is because all the participants in [125] did not use aid.

M-time model has a best cut-off value of 0.43 as identified from the point of intersection as shown in Figure 5.6. For the best cut-off, M-time model yielded both sensitivity and specificity value of 54.99% and the E-score model yielded sensitivity of 67.19% and specificity of 59.43%.

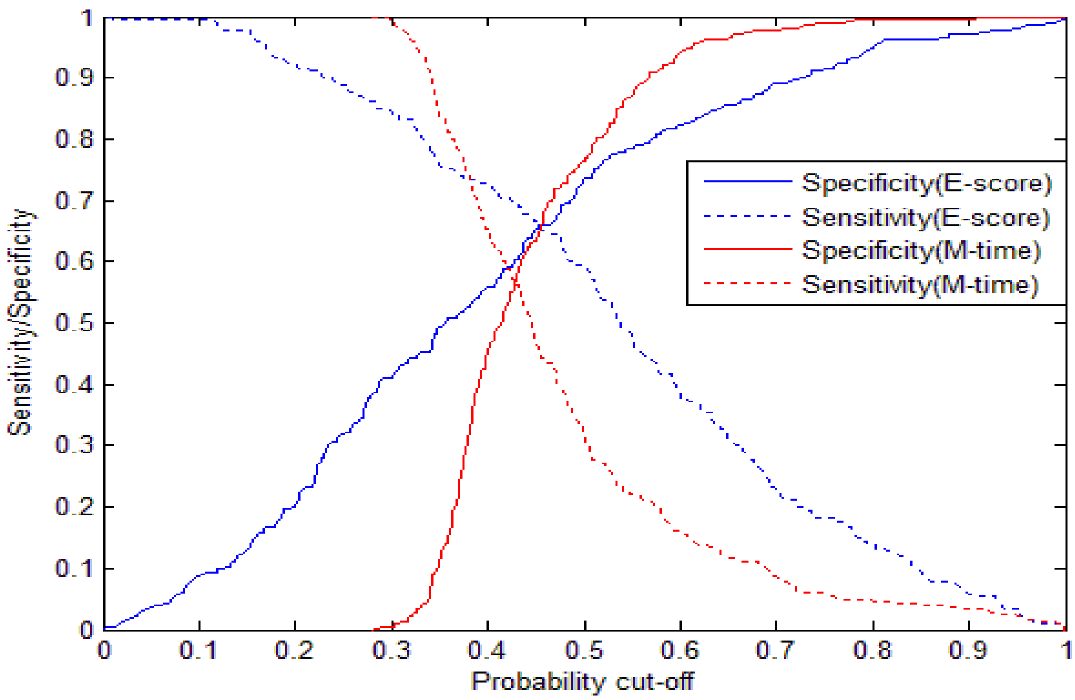

Figure 5.6 Shows the relationship between the sensitivity, specificity and probability cut off obtained from E-score model and M-time model (combined for both groups and gender).Best cut-off is defined as the point where sensitivity and specificity curves intersect.

From Figure 5.6, it is clear that the E-score model outperforms M-time for both the cut-offs described. This shows that developed E-score model is valuable. Comparing the M-time model’s performance for both the cut-offs, it is obvious that cut off determined in the current study shows better performance metrics. This could be because of the difference in participants and instructions given to participants of the studies.

Although, the developed E-score model performs better than M-time, it is still unclear regarding its clinical significance. Further studies are required to examine whether the performance metrics yielded in the study are clinically significant.

5.3. Ability of extracted features for disability level prediction in community dwelling

It is well known that balance and stability are the important factors that reflect falls risk in an individual. Therefore, in this study the features are extracted that reflects balance and stability of the participant during TUG test. The balance impairment is also identified as one of the major risk factors for disability in older adults. Hence, it is worth to explore the ability of the extracted features predicting disability levels of the participants. This investigation is exploratory in nature and it enables analyzing the strength of extracted features beyond falls prediction.

It was already been discussed that quantified assessment of TUG has the ability to predict falls of community dwelling adults. However, following about disability are not yet known

1. Whether TUG test has ability to discriminate disability levels.
2. Whether quantified assessment of TUG test using accelerometer discriminate disability level and has added value.

To investigate these, similar to falls prediction, models were built using the features extracted from the TUG test signal.

5.3.1. Disability level

Disabilities in older adults develop due to a variety of factors, of which balance impairment is one of the major risk factors. Disability in older adults decreases the quality of life, physical functioning cause falls and may even lead to death. Disability has many definitions, the WHO defines disability as any restriction or lack (resulting from an impairment) of ability to perform an activity within the range considered normal for a human being. A disability is said to occur when there is gap between the ability of an individual to perform an activity to the activity's demands [122]. In recent years, many researchers have reported that disability is an important factor in causing health adversities. Assessment of disability level has a paramount value and enables offering timely interventions which may improve general health and also deter falls in future. In order to assess disability levels many qualitative methods such as Expanded Disability Status Scale (EDSS), the Cambridge MS basic score, SCRIPPS scale, World Health Organization Disability Assessment Schedule (WHODAS)and occasionally Barthel Index and functional independence scale are also used cite [126]. These qualitative methods are subjective in nature and do not provide standardized results.

5.3.2. Data

In order to assess the disability level of the participant, 17 basic questions related to activities of the daily living, such as getting in and out from the bed, dressing and undressing, washing face and hands, washing all over, cutting toenails, getting on and off the toilet, going up and down the stairs, getting in and out of chair, feeding self, light housework, heavy house work, preparing and cooking a hot meal, shopping for groceries, taking medication, managing money, getting around the house, walking at least 400 yards [12] was answered by the participant or the care giver. Participants are given a score of either 0 or 1 depending on their ability to complete the task. For an activity that the participant could not perform was given a score of 1. The scores are summed up at the end of all the 17 activities. Therefore the summed scores of disability ranges from 0 to 17, where 17 represents the highest and 0 represents the lowest disability level. Participant demographics are given in Table 5.6.

Table 5.6 Demographics of participants' disability levels separated for male and female

Disability levels	0	1-6	>6	Total
Male	15	81	56	122
Female	13	130	26	199

Similar procedure to falls estimation is followed, as there are more than two categories of disabilities, discriminant classifier is used instead of logistic regression classifier. The TABLE 5.7 compares the results of models built using extracted features and M-time. Considering the pilot nature of analysis accuracy of the models are only compared.

Table 5.7 Accuracy of developed classifier in estimating disability levels

Model	Kruskal-Wallis P<0.01	Best combination of features	Accuracy of developed model	Accuracy of reference feature M-time
Male	{,1-3,34,45-47}	{34,1-3,68}	68.03%	47.54%
Female	{1-3,37-39,45-47,65}	{35}	56.28%	30.65%

The box plot of best combination of features showing its ability to discriminate disability levels is shown in the Figure 5.7.

Kruskal-Wallis is a non-parametric method for testing the measurements whether they are from same distributions. This test is followed as one of dependent variable is binomial (falls) and dependent variable (extracted parameters from accelerometer) is continuous. Moreover, this test is followed as the extracted parameters do not follow normal distribution and has an unequal sample sizes.

Kruskal-Wallis non-parametric test on M-Time yielded a significant p-values of $5.54X10^{-7}$ and $8.44X10^{-12}$ (for male and female participants, respectively) showing its ability in discriminating disability levels. Hence, it is evident that TUG test has an ability to discriminate disability levels.

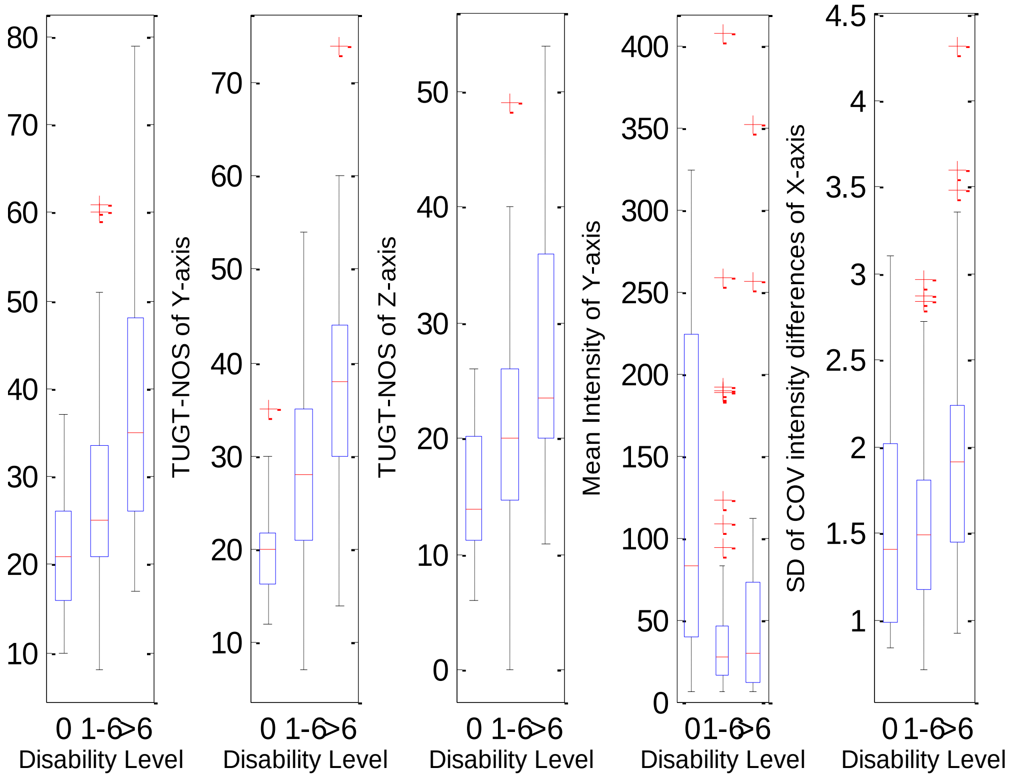

Figure 5.7 Box plot of best combination of features showing it ability to discriminate disability levels in community dwelling

Comparing the classifier models built using features extracted from accelerometer and reference feature which is the time taken to complete the test (M-time). The features extracted from the accelerometer showed a classification mean accuracy of 62.16%, outperforming the M-time (39.10%) classifying disability levels. This shows that quantified assessment of TUG test using accelerometer has ability to discriminate disability levels and has an added value over reference measure M-time.

This chapter at first presents the results of delineation algorithm developed to segment the TUG test sequence from the whole accelerometer recordings. Secondly, it shows the features of importance that have ability to discriminate fallers from non-fallers. Thirdly, it presents the results of the models developed to estimate fallers and it also compares results of the reference feature model with the model developed. Finally, it shows the results that extracted features also have ability to discriminative disability levels in the community dwelling. The next chapter discusses the conclusions and future work.

Chapter 6

6. Conclusions and Future Work

A wrist mounted accelerometer wearable system was developed for assessment of falls risk of community dwelling elderly adults. The developed system was validated with the 394 participants Timed Up Go (TUG) test data collected in the home environment. The system developed is semi–automatic in nature, whereby requiring participants only to tap the sensor system before and after each test.

The absolute error found between algorithmically delineated sequence and reference time was less than 1s which demonstrates that it is practical to semi-automatically estimate falls in the home environment where a strict protocol were followed. The regression model built using best combined features derived from the accelerometer features identified prior falls with a mean accuracy of 66.24%, outperforming manually timed TUG (54.46%). ROC curves derived illustrated that the models built using accelerometer derived features outperform the manually timed TUG in estimating prior falls.

From the results, M-time (Manually timed TUG) has a very high correlation value with the E-time (time that is extracted using the developed algorithm) with a Pearson correlation value of 0.966 ($p<0.001$) combined for groups (With Aid and Without Aid) and genders. In general, most of the selected accelerometer features have correlation values less than 0.5 with the M-time, which shows that the extracted features, holds information independent of M-time. In concordance with [32] and others [37, 47], this study also shows that irrespective of gender and groups, fallers take more time to complete the TUG test than non-fallers. In particular, participants using walking aid (WA) took relatively longer time than those without (WoA).

Not all the features extracted from the signals of accelerometer showed significance in predicting falls. In total, only 32 features out of 95 features extracted from the accelerometer appeared significant estimating falls in community dwelling. It is interesting to see that different features appeared significant for male and female participants; this could be due to the difference in the characteristics of the movements while performing TUG test. It is obvious that the characteristics of the movement of the participant who are using walking aid are different from those who did not use aid and these differences are reflected in the features that are selected by models.

Across both the genders, features namely mean SMPS of Z-axis and SVM, Outlier excluded mean Smps[7] of Y-axis and SVM[8], Outlier excluded mean Intensity of Z-axis and finally TUGT RMS[9] SVM were commonly found significant for the group WoA, whereas for the group With aid, only parameter SD[10] of Intensity difference of SVM was found common. These common features show its importance being consistently

[7] Sum of Magnitude of Power Spectrum
[8] Signal Vector Magnitude
[9] Root Mean Square
[10] Standard Deviation

significant across the models. The reference feature (M-time) was found significant only for female model of the without aid group, for all other gender and groups M-time was found insignificant. In contrast, at least two of the features derived from the accelerometer signals were found significant for all the models developed, refer Table 5.3. This shows that accelerometer derived features are more valuable holding an additional information and can contribute independently to M-time alone to predict falls.

Moreover, the features extracted show capability of predicting disability levels in community dwelling. The results of the models built using the accelerometer features extracted predict disability levels better than reference feature alone. This shows the significance of the extracted features.

From the results of disability level prediction, it can be seen that the higher intensity of TUG signals, lower the disability level. To combine with falls, it is clear that the lower the intensity, the higher the disability level and more prone to falling. This indicates that less energy is expended while performing the TUG which is associated with falls and disability. Similar to the falls, Figure 5.7 shows that higher the NOS, higher the disability. All these results show that falls and disability are directly related although a specific result that describes the relationship between falls and disability is not validated in the study.

The feature selection methodology developed and implemented in the study was robust and independent of the classifier. This is obvious as same procedure is utilised with the linear discriminant classifier to predict disability levels in the community dwelling.

The study suffers from following limitations: Development and adherence to a robust protocol of the test was the most limiting constraint of the study. The threshold values set for taps identification were vague and it was unclear whether these values will suffice identification of all taps in future. As large numbers of samples were used in the study set thresholds could be appropriate for future extractions. In future, prospective evaluation study the protocol definition needs to be improved, such as tap as fast as possible or tap the wrist on the thigh during sitting position this way the taps could be clearly identified using simple algorithm.

The lengths of the TUG signal obtained from different participants were different; this could have affected the frequency spectrum extracted and the windows' sizes utilized for feature extraction remains uncertain. A further study is required to find the optimal window size and this also may further improve performance of the models.

In addition, there are obvious limitations to the study with the analysis exploring association with prior rather than future falls risk. It has been suggested that this may overestimate falls risk [127] in practise. Critically, the approach must be evaluated for prospective falls prediction. It is unclear whether system would yield acceptable performance metrics with prospective falls data.

Although, mean performance metrics across both genders and groups show the E-score model outperforming M-time, for the WoA group the E-Score model improved only sensitivity (for both males and females). Overall, this has resulted in better accuracy and ROC metrics. Favourably, there is scope for the derivation of other parameters which may still improve the performance. Currently, integrated inertial measurements units are developed which comprises of accelerometers, gyroscopes and magnetometers which allows extracting further information from the sensor system which could be useful. The integrated IMU are small and light weight hence it does not cause any restrictions to participants activities. The specific analysis of the segments such as sit-stand, walk, turn and stand-sit may also prove to be valuable; however in this protocol, such segmentation is not achievable but may prove feasible through protocol revision.

Wrist placement promises high universal acceptance. Although, this study has shown improved accuracy for prior falls detection over manual timing alone, it is uncertain whether the wrist is the best location for sensor placement and further study is required to evaluate this. The true clinical value of the results must also be evaluated in a prospective falls prediction study.

TUG test was selected as the assessment task as it is simple, possesses less danger to the participant, reliable and offers potential for automating the falls risk assessment. The task could be revised asking the participant to walk 7 meters instead of 3 meters as this could enable extracting additional reliable features from gait and offer improved prediction of falls.

Previous studies [73, 84, 89, 90] have commonly demonstrated the potential of features collected in a laboratory environment to predict falls risk. The features extracted in studies by Narayanan *et al.* [73] using waist mounted accelerometer and its improvement by Liu *et al.* [128] show good correlation with falls risk. However, the studies are reported utilising a smaller cohort of only 68 participants. Moreover, studies utilises tests such as TUG test, alternate step test and sit-to-stand with five repetitions which is time consuming ,makes harder for the participant to perform the test and therefore becomes less complaint. Performing all the tests in the home environment would require standard equipment for consistent and longitudinal comparative assessment. The tests described places limitations and possess a great challenge to develop consistent and reliable automated algorithm.

Recently, Greene *et al*.[90] estimated falls risk with mean sensitivity of 77.3% and mean specificity of 75.9%, using multiple kinematic sensors placed on the shanks. Utilisation of multiple sensors makes it more intrusive to the wearer, demands more time for attaching and detaching devices, increases the overall hardware cost and is less amenable to automated processing and interpretation.

Weiss *et al.[84]* utilized a single accelerometer to identify fallers (using multiple parameters derived) only from the TUG test and validated the addition of accelerometer has an added value. However, this study validated the hypothesis with 41(23-fallers and 18-healthy) participants. Many features are extracted particularly, features from the sit-stand and stand-sit components of accelerometer signals. The features derived are individually compared whether or not it is able to differentiate fallers from healthy participants.

None of the previous work reported on automation of the falls risk assessment, this current study is the first to report utility of single wrist mounted accelerometer to identify fallers with semi-automated data processing and interpretation. The present study uses large cohort of 394 participants' TUG data collected in home environment, focuses on combining parameters for better classification performance and shows potential for automation. Moreover, the feature extracted in the study proves to estimate disability level of community dwelling participants as well.

A semi-automatic falls estimation of community dwelling older adults was developed using single wrist mounted tri-axial accelerometer. The study utilises data collected from 394 participants performing TUG test in their home environment. Falls prediction models are derived separately for male and female participants using simple logistic regression classifier. Models developed show performance metrics which outperform M-time alone. The study utilises retrospective falls data and its clinical value will be known only during prospective evaluation. Further work will enable to properly establish fully robust protocols and to explore whether improved detection extends to the prospective identification of falls and have clinical significance.

In the present scenario, there is a need for falls estimation system that can discriminate fallers and non-fallers in the community. The requirements of the system that allows to be incorporated in the home environment include:

- Simple assessment task
- Quick to perform the assessment task
- Require little or no external support
- Compatible with the elderly adults
- Reliable and Robust.

Participants using the system require wearing the sensor on their wrist and tapping it before and after performing the TUG test. TUG test is proven to be reliable [32]. The TUG test is definitely simple to perform and it is evident from the 394 participants data (collected from participants aged more than 85 years) of the study. The developed system fulfils the requirements and results shows that it outperforms traditional methodology.

What is clear is that potential for single wrist mounted accelerometer to identify fallers in the community dwelling. The developed system is simple, easy to use, quick, robust, and compliant even for participant of 85+ years of age and can be used in home environment. Falls plays significant role in causing diseases, disabilities and other problems such as fear and restricted activities of living in the elderly. These factors further reduce quality of life in the elderly and make them more susceptible to falling. Moreover, falls impose substantial financial burden to the health care systems. The wrist accelerometer based semi-automatic assessment of falls may enable fallers monitoring in a consistent and minimally intrusive way. This would facilitate efficient and timely intervention for potential fallers beyond the clinical setting. Falls estimation in early would permit offering timely interventions, funds available can be utilised in the other areas of health care and would significantly improve quality of life.

6.1 Future work

The developed accelerometer system shows the feasibility to predict fallers in the community dwelling environment. Even so, there are certain aspects of the study that can be improved. In particular, the features extracted from accelerometers are not associated with specific risk factors of falls such as lower limb mobility, muscle weakness and others. Identifying specific association with factors that causes falls will enable targeted interventions.

The system developed is a first study assessing the value of wrist mounted accelerometer to predict fallers of community. The system requires the data to be transferred for analysis and to produce the results. This can be enhanced by utilising wireless systems to implement data transfer and further processing. Figure 6.1 shows the envisaged falls management architecture. As the user/participant performs the TUG test the data is transferred wirelessly to the base station in the home and then the data is transferred to the cloud processing and storage system. The data uploaded to the cloud system can be accessed securely by doctors with appropriate access to analyse the data and provide a feedback or recommend the participant for targeted interventative treatments. The data can be accessed from anywhere and can be given access to doctors, physiotherapist for analyses and feedback. Therefore falls can be managed more comprehensively and aids timely interventative treatments offered for the elderly individuals.

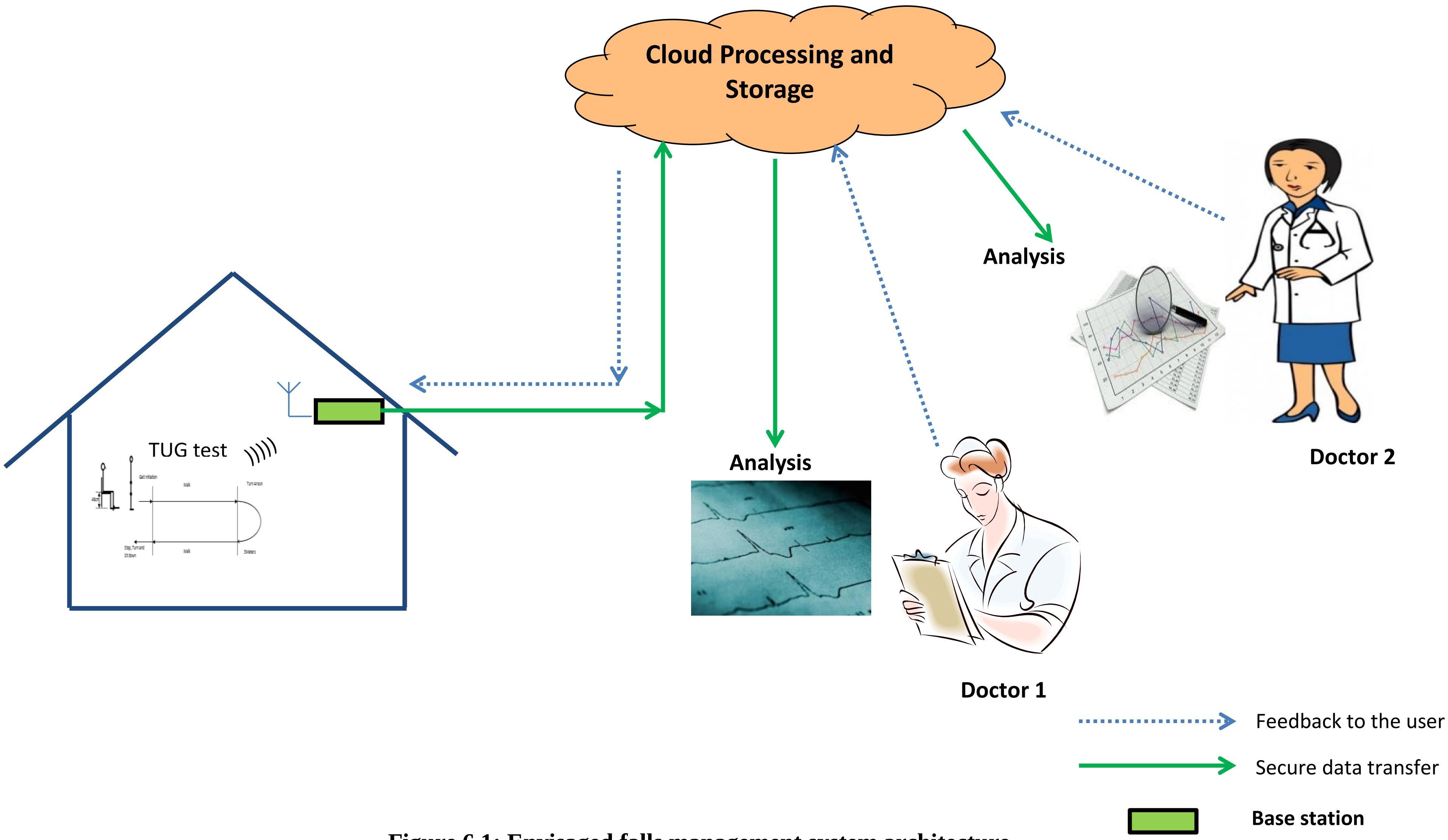

Figure 6.1: Envisaged falls management system architecture

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