Electronic Textile Garments for Fall and Near-Fall Detection

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ABSTRACT

The world population is ageing and one of the biggest detriments to the quality of life of older people is falls. The aim of this thesis is to develop an electronic textiles (E-textile) garment using electronic yarn (E-yarn) technology for near-fall and fall detection. Near-falls are a loss of balance that can be corrected. An increased number in near-falls is seen as a precursor for falls. If near-falls can be detected, hopefully this can lead to fall prevention.

The first step to creating an E-textile for near-fall was to determine the appropriate sensor for near-fall detection. Within the literature there are more studies conducted on fall detection systems rather than near-fall detection. Consequently, both types of system were reviewed. Informed by the literature, it was concluded that an inertial measurement unit (IMU) would be used to manufacturing a motion sensing E-yarn.

Once the sensor had been determined, the optimal placement of the sensor on the body needed to be found. In accordance with the literature six locations were explored, the waist, chest, wrist, lower back, thigh and ankle. A pilot study was conducted, and the results showed that either the waist, thigh or ankle were best.

Interviews and a focus group were held to design an E-textile garment that an older person would be willing to wear. Interviews on clothing preferences, attitudes towards falls, and wearable technology for fall prevention were conducted. Non-functioning prototypes were made and shared with a focus group to determine which would be used in the final design. The design chosen was an over-sock.

Lastly, a functioning E-textile garment was developed and tested on young healthy volunteers. The E-textile garment can accurately classify between three types of activities of daily living and three type of falls with an accuracy of 85.7%. When classifying between ADLs and the falls, the accuracy of detection was 99.4%. Furthermore, when classifying between the ADLs, the falls, and a near-fall event an accuracy of 94.2% was achieved.

This thesis contributes new knowledge to the field of E-textiles by using human centered design to create an E-textile garment people are willing to wear. It also has created the first near-fall and fall detection system in the form of an E-textile and presents the first E-yarn to contain an IMU.

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LIST OF PUBLICATIONS

JOURNAL ARTICLES

Rahemtulla, Z.; Turner, A.; Oliveira, C.; Kaner, J.; Dias, T.; Hughes-Riley, T. The Design and Engineering of a Fall and Near-Fall Detection Electronic Textile. *Materials* **2023***, Vol. 16, Page 1920* **2023**, *16*, 1920, doi:10.3390/MA16051920.

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CONFERENCE PRESENTATIONS

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Hughes-Riley, T., Shahidi, A.M., Marasinghe, K., **Rahemtulla, Z**., Oliveira, C., Dias, T. The development of electronic textiles with sensing capabilities. 3rd Annual Conference on Chemical Sensors for Wearable Devices, 3rd March **2021**, online.

Rahemtulla, Z.; Hughes-Riley, T.; Kaner, J.; Dias, T. Using an Inertial Motion Unit to Find the Optimal Location to Continuously Monitor for near Falls. In *Sheldon 3rd Online Conference Meeting: Solutions for ageing well at home, in the community and at work*; CETEM, **2021**; pp. 135–142.

GLOSSARY

ADL	Activities of Daily Living
ATRG	Advanced Textiles Research Group
BiLSTM	Bi-directional long term short term memory network
ECG	Electrocardiogram
EPSRC	Engineering and Physical Sciences Research Council
E-textiles	Electronic textiles
E-yarn	Electronic yarn
FaME	Falls Management Exercise
HCD	Human-Centred Design
HCI	Human-Computer Interaction
IMU	Inertial Measurement Unit
ISO	International Organisation for Standardisation
LE	Low Energy
LED	Light-Emitting Diode
MATUROLIFE	Metallisation of Textiles to make Urban living for Older People more Independent and Fashionable
MEMS	Microelectromechanical Systems
NHS	National Health Service
NICE	National Institute for Health and Care Excellence
PCB	Printed Circuit Board
PDR Machine	Infrared Spot Reflow Soldering System
RFID	Radio Frequency Identification
SD card	Secure Digital card
UV	Ultraviolet
WHO	World Health Organisation

DATA AVAILABILITY STATEMENT

The data supporting this thesis have been archived and are available to facilitate independent scrutiny of project findings and future reuse.

The data for chapters 3 and 5 are publicly accessible on the open access data repository Figshare and licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). Chapter 3 can be found at https://doi.org/10.6084/m9.figshare.22232482.v3 and Chapter 5 can be found at https://doi.org/10.6084/m9.figshare.21632078.v1.

The anonymised interview and focus group transcripts used in Chapter 4 can be found at https://doi.org/10.17631/RD-2023-0015-DDAT. For legal and ethical reasons, data can be shared upon request for research purposes. Please direct requests to LIBResearchTeam@ntu.ac.uk.

CONTENTS

CHAPTER 1. INTRODUCTION

This thesis presents the design and development of an electronic textile garment for fall and near-fall detection. This involved determining the most appropriate sensor and where it should be located on the body. Using this information, a human-centred design approach was used to design a garment people are willing to wear. Finally, a functional garment was engineered and successfully tested.

1.1 HEALTHY AGEING

The population of the world is ageing due to two major factors: an increase in life expectancy [1] and a decrease in live births [2]. Birth rate is decreasing due to the rise in use of family planning, leading to fewer children, and as a result more women working and being in education [3]. As a result, in 2019, 18.5% of the UK population was aged 65 and over, and this is projected to increase to 23.9% by 2039 [1]. The World's ageing population has a significant impact on the health and social care systems [4] with the cost to the NHS of a 65-year-old being 2.5 times more than that of a 30-year-old [5]. Ageing is usually linked with frailty, which can be defined as a reduction in physical ability, potential for falling and the need for long-term care [6].

Due to the impact of the ageing population, the UK government has a mission to *"ensure that people can enjoy at least 5 extra healthy, independent years of life by 2035, while narrowing the gap between the experience of the richest and poorest"* [7]. Healthy ageing is a concept that is defined by the World Health Organisation (WHO) as *"the process of developing and maintaining the functional ability that enables wellbeing in older age"* [8]. Health is defined by WHO as *"a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity"* [8]. This shows that healthy ageing is about having a good quality of life rather than just being physically well.

1.2 FALLS

Falling is one of the major risks to the quality of life of the ageing population [9]. A fall is defined as "*an event which results in a person coming to rest unintentionally on the ground* *or other lower level, not as a result of a major intrinsic event (such as a stroke) or overwhelming hazard*" [10]. The effects of falling can cause not only serious physical injury but affect mental well-being [9].

1.2.1 Fall Risk Factors

Risk factors associated with falls can be placed into two categories, intrinsic and extrinsic. Intrinsic factors include: age, gender (women have more non-fatal falls than men [9]), chronic diseases, whether they be cardiovascular or neurological, chronic conditions such as arthritis, gait, balance, strength, vision, cognition, dizziness, depression and medications [11]. Extrinsic factors come from the external environment, such as the home environment or inappropriate footwear [11].

Ageing causes a decline in physiological systems, affecting the gait and balance of older people, which can result in near-falls. Near-falls are defined in literature as *"slips, trips, stumbles, missteps, incorrect weight transfer, or temporary loss of balance"* [12]. Near-falls are more frequent than falls, and those who experience near-falls are at a higher risk of falling [12]. Therefore, near-fall detection would be beneficial in the prevention of falls, as caregivers or medical professionals can be informed of an increase in near-fall events.

1.2.2 Impact of Falls

Falling can cause physical injury, such as bone fractures (most commonly the hip [13]) or brain injury [14], non-physical injuries including long lie [15], fear of falls and loss of confidence [11], and mortality in extreme cases [9]. Hip fractures are estimated to cost over £1 billion per year to health and social services in the UK [13]. Hip fractures in over 65s are more common in women as they are more likely to develop osteoporosis than men [13]. It is estimated that only 36 % of older people return to independence after a hip fracture [16].

Age UK has created a factsheet on the impact of falls on older people [13]. This factsheet states that falls cause the most emergency hospital admissions in the over 65s age group. In 2017/2018, there were 218,000 emergency hospital admissions for over 65s because of a fall, of which 68 % were aged over 80 [13]. In addition, at least once a year, a third of those over 65s and half of those over 80s fall. Within hospitals, more than 680 patients in England fall per day [13]. Fall risks within the home are estimated to cost NHS England £435 million per year, yet these are only the falls that are reported, which are estimated to be only 25 % of total falls [17].

Detecting a fall is important, as it will reduce 'long lie', which is described in the literature as involuntarily lying on the floor for an hour or more following a fall [15]. 'Long-lie' is a serious condition, which can lead to other health problems even when no physical injury occurred. The quicker a fall is detected, the lower the likelihood of serious complications and damage to mental health, which could prevent further falls [10]. Therefore, the ability to remotely monitor for fall detection would reduce pressure on both hospitals and social services. However, it will not prevent the risk of falls, which can cause physical injury.

1.2.3 Preventative Measures

Currently, fall risk in the UK is measured using guidelines provided by the National Institute for Health and Care Excellence (NICE) in 2019 [18]. These guidelines include a risk assessment to be performed by an experienced clinician that covers a variety of factors and physical tests such as 'Timed Up and Go' and 'Turn 180°'. The disadvantage of these assessments is that they are subjective and their interpretation will depend on the clinician. Additionally, the assessment is only carried out if the person has already had a fall or has certain conditions which could lead to a fall, such as Parkinson's disease. However, this does not mean that a fall will not happen without these risk factors. A study from 2019 found that most GPs do not have enough time during patient visits to identify risk factors before a fall occurs [19]. Therefore, there are low referral rates to fall prevention programmes [19], such as the Falls Management Exercise (FaME) toolkit or the Otago programme.

The FaME toolkit [20] is an evidence-based programme that uses strength and balancing exercises for fall prevention. This toolkit not only keeps older people active but allows them to be social, which helps keep them independent. The Otago programme [21] is an at-home programme for strength and balance training that has been shown to reduce falls in older people by 35 %. Both the NHS [22] and Age UK [23] recommend strength and balance training for fall prevention.

1.3 Research Motivation

The motivation for this research is that falls can be detrimental to the quality of life of older people, as well as costly to the NHS. Even if people are not physically injured, they can be left with mental health issues that impact their quality of life. **Creating a remote monitoring device to detect near-falls and falls would be beneficial to help reduce this impact.**

Wearable technology can be used in real-time to non-invasively monitor various measurands including heart rate, heart rate variability, temperature, blood oxygen saturation, respiration rate, blood pressure, and human motion [24]. Wearables can either be in the form of accessories, such as a fitness tracker, placed directly onto the skin, or embedded into textiles to be worn.

The current commercially available wearable products do not detect near-falls; therefore, they cannot be used for preventative measures. The current products take the form of watches [25,26], panic buttons (which require the person to press a button) [27,28], and pendants [29,30]. Most of these products do not state how they work (sensors or analysis). The Apple Watch states that it detects hard falls and the more active you are the more likely it is to detect a fall. To do this, it uses the accelerometer and gyroscope already present within the watch. This information suggests that the Apple Watch uses an acceleration threshold rather than a machine learning algorithm for detection, and thus smaller falls may be missed. In the case of the panic button, if someone falls, they may lose consciousness so they cannot press the button. The pendant is worn around the neck and a study by Fang [31] showed that wearables around the neck are annoying and uncomfortable to users and the wrist is the most desirable location. The aesthetics and comfort of the devices are important design considerations [32].

The advantage of electronic textiles (E-textiles) for fall detection in comparison to currently available devices, is that they are flexible and inconspicuous, making them comfortable and more likely to be worn. The Advanced Textiles Research Group (ATRG) at Nottingham Trent University has successfully embedded sensors into yarn form to create electronic yarns (E-yarns) [33] that can be woven [34] or incorporated into knitted [35] fabrics. The standard construction process of E-yarns involves three stages [35]: Firstly, the required commercially available electronic component is soldered onto multi-strand copper wire (such as seven-strand copper wire, strand diameter = 50 µm, KnightWire, Potters Bar, UK) using an infrared reflow soldering process (for example using a PDR IR-R3 Rework System, PDR, Crawley, UK). For the second stage of construction, the soldered component and solder pads, along with eight textured, multifilament polyester yarns (Ashworth and Sons, Cheshire, UK) that are equally spaced around the chip, are placed inside an appropriate diameter Teflon or silicon tube. A curable polymer resin (9001-E-V3.7, Dymax, Corporation, Torrington, CT, USA) is then injected into the tube and exposed to a UV light source (BlueWaveTM 50, Dymax Corporation Torrington, CT, USA) to cure the resin. During the final stage, the encapsulated component is inserted into a braiding machine (RU1/24-80, Herzog GmbH, Oldenburg, Germany) or a knit braiding machine (RIUS MC braiding machine, RIUS, Barcelona, Spain) to produce the final E-yarn. The advantage of E-yarns over many other electronics integration techniques for textiles is that they do not change the behaviour of the fabric and they are inconspicuous within the fabric. **Error! Reference source not found.** shows the manufacturing process of E-yarns as well as a LED E-yarn woven into a top.

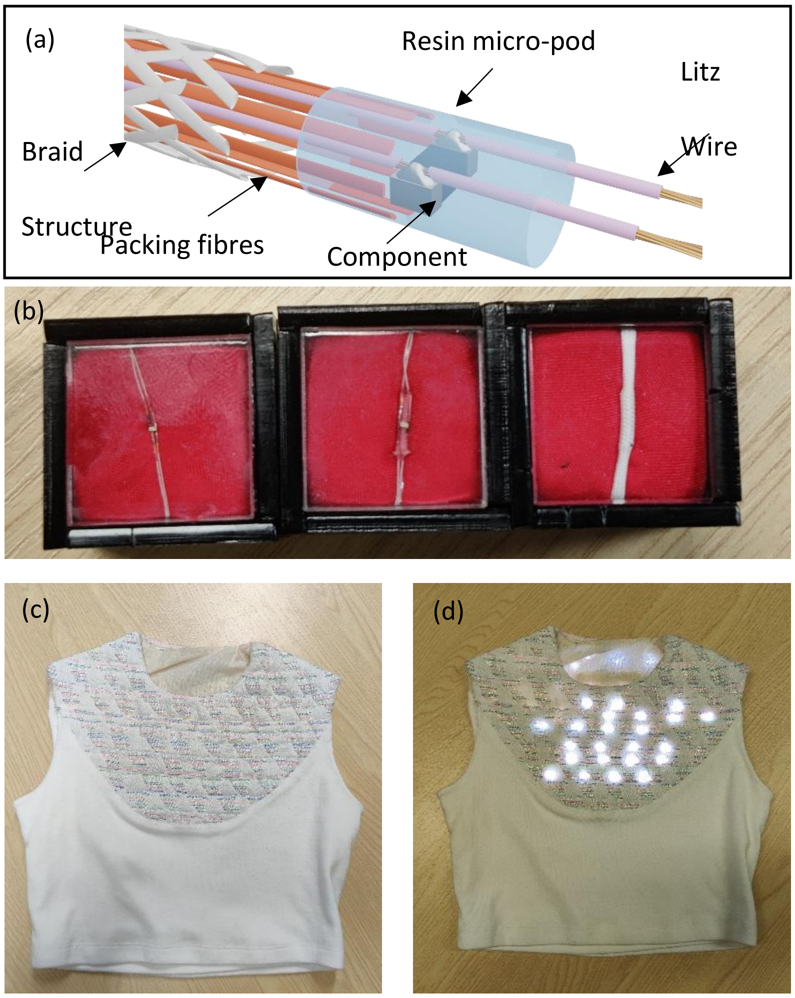

Figure 1.1 (a) Schematic of an LED E-yarn drawn by Kalana Marasinghe. (b) The manufacturing process of an LED E-yarn, from left to right, the soldered stage, the encapsulated stage and the final E-yarn developed by the ATRG. (c) Image of a top containing LED E-yarns and (d) is an image of a top with the LED E-yarns illuminated. The top containing LED E-yarns was woven by Matholo Kgatuke for the ATRG.

Presently, most studies use a fixed threshold value to detect a fall [36]. The fixed threshold value used varies across publications and cannot be used for different people as factors such as height and weight will affect the person’s motion [36]. Other approaches have been explored to solve this issue; these include using an adaptive threshold and the use of machine learning algorithms, which clearly show that personalisation is crucial when creating a highly accurate system [36]. For near-fall detection, machine learning is critical to detect the difference between activities of daily living (ADLs), near-falls, and falls for each individual [12].

The knowledge gap in the literature that this thesis aims to fill, is using a human centred-design approach to create a functional E-textile garment people are willing to wear. In addition, finding the most appropriate sensor as well as the optimal placement of the E-textile on the body for near-fall and fall detection. Fall and near-fall detection studies do not clearly define the placement of sensors for the most accurate monitoring. Most studies use different placement and sensors or sensor fusion without obvious reasoning. Therefore, the research will find the most appropriate sensor or sensor fusion and the optimal placement for near-fall detection. Chapter 2 contains the literature review that develops these claims further. In addition, the majority of the fall and near-fall detection studies focus on machine learning. This research takes a more holistic approach by exploring the needs and wants of the end user to design the E-textile garment. Chapter 4 presents interview and focus group data used that informed the final E-textile garment design.

1.4 AIMS AND OBJECTIVES

The main aim of this research was to develop an electronic textile system for near-fall detection. To address this overall aim, four research questions need to be answered; each question has linked objectives that are needed to address these questions.

RQ1: What are the most appropriate sensors or combination of sensors for the accurate detection of near-falls?

- Decide what factors will be useful to measure, to ascertain which sensors or combinations of sensors will produce the greatest accuracy and reliability.
- Understand whether to use a single sensor, multiple sensors of the same type or a combination of different sensors.

RQ2: Where is the most appropriate placement for the sensor(s) on the body?

- Find where on the body the sensor(s) should be placed to achieve the most accurate and reliable results, whilst still being comfortable and unobtrusive.

- Determine if the sensor(s) need to be placed at multiple sites on the body to distinguish between a fall, a near-fall and activities of daily living (ADL).

RQ3: How to design an E-textile garment that older people are willing to wear for fall and near-fall detection?

- Determine the design limitations imposed on the E-textile to provide accurate data.
- Ask people how they feel about fall prevention and if they would be open to wearing an E-textile garment
- Create prototypes based on older people's opinions and determine what is desirable.

RQ4: Does the final E-textile garment function as designed?

- Create electronic yarns and test to see if the behaviour of the sensors is affected by the production process.
- Incorporate the electronic yarns into one of the prototype garments.
- Test the effectiveness of the garment by conducting a user trial with healthy volunteers.
- Design the final garment containing the required sensor, a power source and a way to collect and transmit the data.

1.5 METHODS

Four stages needed to be achieved for the successful outcome of the thesis, which is detailed below.

1.5.1 SELECTING A SENSOR

The first stage of this thesis was to determine which sensors should be tested. From the literature, it is known that the following types of sensors are used for fall and near-fall detection: analogue and digital accelerometers, gyroscopes, pressure sensors, and inertial measurement units (which contain a combination of sensors) [10,12].

A variety of different sensors had been purchased initially to be tested. These included an analogue and digital accelerometer, the ADXL337 and the ADXL345 [15,37,38] as well as a selection of inertial measure units (IMUs). It was difficult to purchase gyroscopes alone, and those that were available were not small enough in size for E-yarn manufacturing. The ADXL337 has previously been embedded within a yarn to create vibration-sensing E-yarns for the monitoring of hand-transmitted vibrations [39]. The ADXL337 is similar to the ADXL335 [40], which has been used in the literature for fall detection, suggesting that this accelerometer should be appropriate for this application. A combination of sensors, such as accelerometers and gyroscopes are frequently used for fall detection to provide an accurate indication of whether a fall has occurred [10,36]. Also, they are found in all modern smartphones, therefore various studies have been performed using smartphones for fall detection [36,41,42].

Ultimately, for this study, an IMU, which is a combination of an accelerometer and a gyroscope in one unit, was chosen and tested based on the literature. These are commonly used in fall detection studies [43–45] and tend to provide more accurate results than accelerometers alone [10]. In addition, they are almost exclusively used in more recent near-fall detection studies [46–50] due to the compact size of the IMUs they are easier to turn into E-yarns, which simplified the fabrication of the electronic textile.

1.5.2 Determining Experimental Parameters

The second stage of this thesis was to determine where the sensor(s) should be placed on the body without being intrusive yet still giving accurate results and the sampling rate. As an IMU was used in the study, the results were also used to determine whether both acceleration and angular velocity data were needed. This work was undertaken as within the literature with each study using different parameters, with little or no reasoning given.

A pilot study was conducted to help determine sensor placement on the body and whether more than one sensor is required. Furthermore, it was used to establish whether both acceleration and angular velocity data were needed. For the pilot study, the commercially available MetaTracker produced by MbientLab was used as it contained an IMU (BMI160). In addition, MbientLab also provided the software to collect the data from the MetaTracker. To validate the data a video was taken during the trial.

The participants recruited for the pilot study were five young healthy volunteers aged between 22-31. They were young adults because it would not have been ethical to have older adults (65 and over) falling onto a crash mat for a proof of concept. The participants were equipped with the sensors at pre-determined locations: waist, chest, lower back, wrist, thigh and ankle. Within the literature, the placement varies and there is often a lack of reasoning for the placement chosen. Therefore, these experiments were vital in establishing the correct location for accurate measurements for fall detection and establishing this knowledge will help the wider academy. Common placement for accelerometers are: the waist, chest and wrist for fall detection. For near-fall detection, the common positions on the body are lower back, chest, waist, ankle and thigh. A few studies have used accelerometers on the ankle as well as other locations without successfully identifying the optimal location for activities of daily living (ADLs) [51] or fall [52].

The participants were asked to perform basic tasks such as walking, kneeling, sitting on a chair and stool, lying down, reaching high and low, ‘Timed Up and Go’ tests (standing from seated, walking and returning to seated), ‘Turn 180°’ and falling onto a crash mat. Activities of daily living (ADLs) are essential skills required to live independently [53]. Walking, sitting down on a chair and stool, kneeling, lying down and reaching high and low are tasks that mimic ADLs. As mentioned earlier, the ‘Timed Up and Go’ and ‘Turn 180°’ tests are used by clinicians for fall risk assessment [18]. To validate the data measured, a video camera will be used to record volunteers performing the different activities.

During the analysis of the data of the pilot study, it became apparent the data was not accurate. However, Nottingham Trent University had implemented restrictions that stopped further experimental work with face-to-face participants due to the COVID-19 restrictions. Therefore, a set of validation trials was conducted using one participant. These validation trials used the MetaTracker along with the Bosch developmental kit that included the BMI160 shuttle board and Bosch software to run collect the data. This was chosen as it contained the same model of IMU as the MetaTracker.

In the validation trial, the participant was only asked to perform the walking, kneeling, reaching high and low, lying down and ‘Timed Up and Go’ activities. The locations of the MetaTracker used were the waist, thigh, and ankle. All the activities and locations were not used as they were not required for the validation. The Bosch hardware was used at the thigh to test different sampling rates. This was not possible in the pilot study due to technical difficulties with the MetaTracker and the software.

The validation trials confirmed the data from the pilot study and the data from both was visually analysed. As the participants were only asked to fall, the data was used to narrow down the optimal sensor placement as well as whether both acceleration and angular velocity are required for near-fall detection.

1.5.3 Finding What People Want

The third stage of the thesis was a collaborative project to investigate attitudes, habits, and preferences concerning clothing, technology and monitoring devices of older women to inform the development of the E-textile garment for fall and near-fall detection. This project utilised a human-centred design approach by initially conducting semi-structured interviews online with 12 participants aged between 65 and 84. Although the pilot study was performed by younger women, as the final garment was meant for older women, it was important to understand their needs and wants. Due to COVID-19 restrictions, it was difficult to access more women through charities such as Age UK. Therefore, to recruit the participants for the interviews, the snowball sampling method was used [54].

The areas of focus in the interviews were clothing preferences, attitude towards technology, ideas on wearable technology and placement, which lead to more specific questions on fall prevention and placement of sensors based on the pilot study. The data collected was analysed and used in a design sprint that involved a four-person team. This was a multidisciplinary team with expertise in E-textile development, E-textile design, textile and fashion design, seamless knit manufacturing, and pattern cutting. Three prototypes were produced based on the interview data and the locations determined by the pilot study.

Once the prototypes were developed, they were presented to a small focus group of five women to provide feedback. The focus group was held in person at Nottingham Trent University to allow the women to handle prototypes. From the interviews, it was clear that they were unfamiliar with E-textiles, and it was most productive to gain feedback in person. The women that attended the focus group were close to Nottingham and comfortable with being close to strangers. The data collected from sharing the prototypes with the participants was used to determine which prototype would be made functional.

1.5.4 Developing and Testing the Functional prototype

The fourth stage of this thesis takes the information from both the second and third stages to develop the final functional garment design. The first step to developing a functional prototype was to construct the E-yarn. The sensors: ADXL345, ADXL337 and BMI160 were initially tested to see if they could be incorporated into an E-yarn. Different techniques were investigated to create an E-yarn. These included soldering using the PDR machine and developing a small, printed circuit board (PCB) to attach the sensor to PCB using conductive glue. The final technique was directly soldering Litz wire onto the sensor using a soldering iron, which was successful. As a result of the sensor shortage, the IMU that was used was the MPU-6050.

The method of constructing E-yarns is non-standard and may change the behaviour of the sensor. Once a soldering technique had been determined the MPU-6050 was tested at different stages of construction as well as in the final prototypes design. To measure the behaviour of the sensor, two test rigs were developed, one for acceleration and one for angular velocity.

Once the final E-yarn had been established and tested, the hardware module was developed. This required finding the correct microcontroller and designing and making a small PCB according to the sensor's datasheet, to ensure it worked correctly and accurately. Due to the technical issues in the pilot study, the hardware module was wired to a laptop to collect the data.

Finally, with a functional E-yarn and hardware module, the e-textile prototype was tested similarly to the pilot study. Thirteen healthy female volunteers aged between 22 and 33 were recruited for the trials. Similar to the pilot study, young women were chosen as this is a proof-of-concept and it would have been unethical to have older women fall and perform near-falls without knowing if the E-textile would work.

Each participant was asked to perform seven activities, walking with a turn, the 'Timed Up and Go' test, controlled stumble and three types of falls onto a crash mat (sideways, backwards and forwards). These were chosen based on the results of the pilot study. As before, to validate the data a video was taken during the trial. The data collected from the trials was visually analysed and input into a machine learning algorithm to determine the accuracy of the prototype to classify ADLs, falls and near-falls.

1.6 Structure of Thesis

The thesis contains six chapters that are outlined below:

Chapter 1: Introduction - This chapter provides the context for this work. It introduces the ideas of healthy ageing and the impact that is caused by a fall in older people, which is the motivation for this research. It also touches on the knowledge gaps that exist and based on these the research questions and objectives are defined. Finally, the last section details how the research question will be tackled.

Chapter 2: Literature Review – This chapter details the work that is currently being done in fall and near-fall detection in academia and what is commercially available. It shows that the main focus for fall and near-fall detection is on the machine learning algorithms and not the hardware or design. As this research takes more of a holistic approach, electronic textiles are explored as they are a potential solution for wearable fall and near-fall detection that might be worn. In addition, the use of human-centred design in textiles specifically for older adults is explored. Currently, at the time of writing, the author knows of no other research that is focused on creating a wearable device based on human-centred design or an E-textile fall detection system. This chapter also answers one of the research questions on sensor choice (**RQ1**).

Chapter 3: Optimal placement of an inertial sensor for fall and near-fall detection – This chapter details a pilot study that involved young healthy volunteers. The results of this pilot study determined optimal placements for the sensor, the number of sensors required, as well as the experimental parameters needed for further human trials (**RQ2**).

Chapter 4: The design process of E-textiles for fall and near-fall detection – This chapter focuses on using human-centred design as a methodology to design the final E-textile garments. It showcases interview data taken from adults over 65 that was used to create three prototypes. These were then shown to a small focus group that allowed the final design to be determined (**RQ3**).

Chapter 5: Development and testing of the final E-textile design – This chapter covers the manufacturing of the E-yarn, testing of the E-yarn, development of the hardware module and creation of the final prototype. In addition, it details a human trial performed with young healthy volunteers, modelled on the pilot study in Chapter 3 and shows the accuracy and reliability of the E-textile system for detection. This study showed that falls, near-falls and ADLs can be differentiated with an accuracy of 94.2% (**RQ4**).

Chapter 6: Discussion – This chapter demonstrates how the research has addressed the research gap identified at the end of the literature review. It illustrates how the research is similar and different to what has been done before, as well as the significance of the research and how it could be applied more generally.

Chapter 7: Conclusion – This chapter summarises the conclusions from this research and suggests future work that can be done to develop this work further.

1.7 COVID STATEMENT

This thesis was completed from June 2019 to March 2023, which was affected by the COVID-19 pandemic. National lockdowns were in effect between March 2020 - June 2020 and January 2021 – July 2021. There were additional restrictions in place with no access to the University between March 2020 – September 2020 and December 2020 – March 2021. The main aim of this thesis, which is to develop an electronic textile for near-fall detection was not altered however, the research methods were. The original research plan for the thesis included:

- Testing a variety of sensors that are used in the literature to determine the most appropriate sensor.
- Finding the most suitable placement of the sensors and how many would be required for the most accurate detection.
- Developing the most accurate method for classification between activities of daily living, near-falls and falls.
- Fabricating several textiles of different materials to test the durability of the electronics within the textile.

The plan was modified due to the lockdowns, which closed the lab in total for nine months and prevented experimental work from being conducted. In addition, there was a shortage of all inertial sensors that were required for this thesis due to the pandemic and is further discussed in Chapter 5. Consequently, the literature was used to determine the most appropriate sensor.

However, it was impossible to find the most suitable placement for the sensors within the literature, which resulted in the pilot study presented in Chapter 3. This study was completed in between the two lockdowns in the UK. This limited the number of people that could be recruited due to the health and safety restrictions in place at the time. Whilst reviewing the literature on fall detection it became clear that this is the focus of the studies was creating the most accurate classification technique.

In addition to the sensor shortage, the sensor that was chosen for the experimental work went out of stock. Therefore, there were not enough sensors to conduct any durability testing. that could be purchased. To combat this, the research plan was altered to include a human-centred design approach to create a garment people want to wear. Ultimately, this was a benefit to the thesis as within fall and near-fall detection this has never been the focus.

Similarly, within the electronic textiles field, there has been a lack of research into what people want [55,56]. To the knowledge of the author, the MATUROLIFE study is only research in the field of E-textiles that uses co-design as a method to develop devices [57].

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CHAPTER 2. LITERATURE REVIEW

2.1 INTRODUCTION

This chapter reviews the literature on fall and near-fall detection studies that used wearable sensors. The sensors used for fall and near-fall detection have also been used for gait measurement studies. Gait here refers to the pattern of walking, and the measurement of gait concentrates on limb movement during the gait cycle [1]. Although there is a link between gait abnormalities and falls, these tend to be from neurological conditions [2]. As this thesis is focused on the detection of near-falls for healthy ageing, studies that include people with neurological conditions are excluded. Subsequently, this chapter describes electronic textiles (E-textiles) and their development, including the use of electronic yarns (E-yarns). Lastly, E-textiles for healthy ageing and motion are discussed.

2.2 FALL AND NEAR-FALL DETECTION

Three review papers [3–5] have been studied to learn about fall detection work that informed the research design of this thesis. Generally, studies on fall detection have been conducted using: wearable devices such as smartphones or smart watches, ambient sensors such as pressure sensors or microphones and vision-based sensors such as cameras, thermal or infrared sensors [3–5]. These fall detection reviews discuss various methods and sensor types for fall detection. Both ambient sensors and vision-based sensors detect by sensing the environment of the user, ultimately requiring them to be fixed indoors within the home, usually in one room. This is disadvantageous as it limits the areas where detection can take place. Additionally, ambient sensors can easily be affected by the environment in which they are placed, and vison-based sensors have privacy issues associated with their use [3,4]. Therefore, for this thesis, wearable sensors are the focus, so that near-falls can be detected as a person is within but also outside the home. The accuracy of fall detection is improved by using a combination of sensors including gyroscopes, magnetometers, and barometers which have been discussed within the literature [3,4]. In most studies, a fixed threshold value is used. However, this value either is not mentioned or varies in the literature. This is because factors such as height and weight affect motion. Alternative methods have been studied including adaptive thresholds and machine learning which allow for personalisation for the individual, giving more accurate results [3,4]. Nooruddin *et al*. [5] also concluded that machine learning gives the highest accuracy for fall detection rather than the number of sensors used. Additionally, most studies only test their algorithms on their dataset, although it would also be beneficial to use open-source datasets to test these algorithms. There are several available fall detection datasets for wearable fall detection which are presented in Table 2.1 below.

Table 2.1 List of available fall detection datasets using wearable inertial sensors

Dataset	**Sensor**	**Placement of inertial sensor**	**Participant age**
KFall [6]	IMU	Low back	Under 65
SisFall [7]	Accelerometers and gyroscope	Waist	Under 65 and 65 plus
DLR [8]	IMU	Waist (belt)	Under 65
MobiFall [9]	Smartphone	Trouser pocket	Under 65
tFall [10]	Smartphones	Trouser pockets	Under 65
UMAFall [11]	Smartphone and IMUs	Right thigh pocket, ankle, waist, chest and wrist	Under 65
Vilarinho *et al*. [12]	Smartwatch and smartphone	Wrist and thigh pocket	Under 65
UniMiB SHAR [13]	Smartphone	Trouser pocket	Under 65
Wertner *et al.* [14]	Smartphone	Hip	Under 65

The datasets included in Table 2.1 are only for wearable inertial sensors, and inertial sensors within smartphones and smartwatches. They all compare ADLs and falls. Any datasets that do not include falls have been excluded.

Near-fall detection papers are limited, as the review paper by Pang *et al*. [15] published in 2019 gives a clear example of this. In this review paper, only nine articles were found to meet the criteria of the review. This review paper showed that like fall detection studies, various locations for the sensor placement were chosen including the head, chest, waist, thigh, ankle, trouser pocket, and shank, the most common location being the waist (seven of the nine had a sensor on the waist). All the studies used accelerometers and five of the nine also used gyroscopes. All of the data was collected in a laboratory setting with young adults and the near-falls were not compared to falls. For this thesis, a review was conducted, using search terms taken from Pang *et al*.[15], and found six additional articles from 2016-2022 [16–21]. All but one of the six pieces of work used one or multiple IMUs. The focus of the work was to develop the most accurate detection system, without considering the needs and wants of the end user.

While searching for near-fall detection articles, many papers about pre-fall or pre-impact were also found. A near-fall is described as a slip trip or imbalance that can be corrected [15]. However, within fall detection and near-fall detection studies, pre-impact or pre-fall refers to the time before the fall. One reason to determine the moment before the impact of a fall occurs is to deploy an airbag to prevent injury [16,22,23].

2.2.1 Experimental Parameters

This section of the literature review examines the experimental parameters used for fall (Table 2.2) and near-fall detection (Table 2.3) studies. These parameters were studied as they were used to inform sensor selection as well as the design of the human trials presented in Chapters 3 and 5.

2.2.1.1 Fall

Table 2.2 presents experimental parameters taken from a range of fall detection studies. It should be noted that all inertial sensors are 3-axis unless it has been stated otherwise within the table. An IMU is an inertial measurement unit, Acc stands for accelerometer, Gyro stands for gyroscope and Mag stands for magnetometer.

Table 2.2 Experimental parameters taken from fall detection studies

Authors	**Sensors**	**Placement**	**Sampling Rate**	**Activities**	**Ages**	**Classification Method**
Kangas *et al.* [24]	Acc (ADXL330)	Waist	50Hz	6 Falls 4 ADLs	40-98	Threshold
Wu *et al.* [25]	IMU (MPU-6050)	Waist & right thigh	100Hz	2 Falls 7 ADLs	20-27	Machine learning
Wu *et al.* [26]	IMU (MPU-6050)	Left wrist, right arm, waist, left	100 & 20Hz	4 Falls 3 Near-falls	20-27	Machine learning

		shank, right thigh & front head		7 ADLs		
He *et al.* [27]	Acc & Gyro	Top of a vest	100Hz	2 Falls 4 ADLs	20-45	Machine learning
Albert *et al.* [28]	Smartphone (Acc)	Back	15-25Hz	5 Falls Wore for a week	22-50	Machine learning
Choi *et al.* [29]	Acc & Gyro (2-axis)	Chest	Not stated	4 Falls 3 ADLs	Not stated	Machine Learning
Bourke *et al.* [30]	Gyro ADXRS300 (2-axis)	Chest	1kHz	4 Falls 8 ADLs	21-29 70-83	Threshold-based algorithm
Quadros *et al.* [31]	Acc (ADXL345), Gyro (L3G4200D) & Mag (HMC5883L)	Wrist	100Hz	6 Falls 6 ADLs	26.09 ± 4.37	Threshold & machine learning
Nho *et al.* [32]	Acc (EBIMU24GV4) & heart rate sensor (HRM-2511B)	Wrist	50Hz	6 Falls 9 ADLs 4 Fall-like activities	25.8 ± 3.6	Machine learning
Otanasap *et al*. [33]	MetaTracker (Acc)	Chest	Not stated	4 Falls	19-21	Dynamic threshold
Özdemir *et al.* [34]	MTw sensor unit (Acc, Gyro, Mag)	Head, chest, waist, right thigh, right ankle	25Hz	20 Falls 16 ADLs	M - (24±3) F - (21.5 ±2.5)	Machine learning

The article by Wu *et al*. [25] concluded that placing the sensor in multiple locations would allow for a new way to identify falls before impact, using their method for classification. Three other studies presented above also use the idea of classifying the moment before the impact of a fall as pre-fall within their algorithms [29,30,33]. Another article by Wu *et al*. [26] also talked about using multiple sensor placements to get the best sensitivity and specificity.

Similarly, Özdemir *et al*. [34] looked at multiple sensor placements but thought that it would be beneficial to look at vital signs and audio sensors. On the other hand, in the article by He *et al*. [27] the placement of the sensor used was at the top of a vest (where the label would go). However, within this paper, they also stated that the upper trunk is the best placement for the sensor. The reasoning as to why the vest was chosen is not given. This could be because the focus of all the studies was not on the design of the hardware or what the final product would be, but rather on the accuracy of the detection. Only Albert *et al*. [28] acknowledge that a limitation to their accuracy is the very specific placement of the sensor. For this study, each participant wore their phone on their back. Additionally, is it not a realistic place for people to keep their phones. One study [31] mentioned the reason for the placement of the sensor selection at the wrist, as it is seen as discrete and likely to be accepted by users. However, they did not conduct their research and have not referenced related work.

2.2.1.2 NEAR-FALL

The experimental parameters for near-fall detection studies are presented in Table 2.3. These are taken from six articles found for near-fall studies using wearable sensors. To the knowledge of the author, these are the only near-fall detection studies that were conducted from 2016-2022. An IMU is an inertial measurement unit and Acc stands for accelerometer.

Table 2.3 Experimental parameters taken from recent near-fall detection studies

Authors	**Sensors**	**Placement**	**Sampling Rate**	**Activities**	**Ages**	**Classification Method**
Ojeda *et al.* [19]	IMU	Feet, low back and wrist	128Hz	Loss of balance whilst at home	66-71	N/A
Choi *et al*. [16]	IMU (MPU-6050)	Waist	40Hz	16 ADLs 10 Near-falls 10 Falls	21-34	Machine learning
Noureda-nesh *et al*. [17]	IMUs	Ankles, thighs & lower back	128Hz	8 classes of near-fall perturbati on	26 averag e	Machine learning

Wang *et al*. [18]	Acc	Lower back	100Hz	Near-fall perturbation	60 and over	Machine learning
Aprigliano *et al*. [21]	IMUs	Pelvis, thighs, shanks & feet	100Hz	Near-fall perturbation	25.9 ± 2.8	Machine learning
Hauth *et al*. [20]	IMUs	Feet &lower trunk	100Hz	Loss of balance whilst at home	Elder adults	Machine learning

In the more recent articles shown in Table 2.3, half of the studies recruited older people [18–20], rather than using young adults for the trials. Three of the studies had the participants slip or trip unexpectedly whilst on a treadmill or specialised platform, as a way to simulate near-falls [17,18,21]. Two of the studies allowed the older participants to wear the IMUs at home and record their loss of balance on a voice recorder [19,20]. Only one of the six studies simulated near-falls [16]. This was accomplished by showing the participants a pre-recorded video demonstration that detailed each activity. This study was able to accurately differentiate near-falls from ADLs and falls. In addition, it looked at the pre-fall phase of the fall with the idea of deploying an airbag to prevent injury.

2.2.2 Commercial Products for Fall Detection

In order to develop a more suitable fall and near-fall detection device it is first important to understand what is currently available commercially. There are various fall-detection devices on the market. Most of them are features included with smartwatches: for example, Apple Watch 4, Samsung Galaxy Watch 4 and Garmin Forerunner 945. Other wrist-worn device examples include the Vibby Fall Detector [35] and Minuet Watch [36] sold by Tunstall, as well as the Buddi Connect and Buddi Clip [37]. All of these devices can also be worn around the neck. In addition, there are camera-based solutions and one example of this is the Ezviz C6 [38].

Furthermore, as smartphones contain much of the same technology as smartwatches, multiple fall-detection apps have been developed and can be downloaded. An example of one of these apps is Chk-In Fall Alert, which claims to automatically detect falls. However, on the Google Play Store, it only has a rating of 2.6 stars and one reviewer said "*Cannot establish* *an account. Cannot connect to the server. Says to check the Internet connection. Internet works for all other apps"* [39]. In addition, on the Apple store, it has a rating of 1 star [40]. FallSaftey [41] is another app that has been developed, that has a higher rating of 4.1 stars. However, this app is only available on Apple devices.

As shown in the literature, some devices are being developed that inflate an airbag when a fall occurs to prevent injury. The device that is presented here was created by Wolk [42] (The Hague, Netherlands). They have designed two devices, a belt and shorts, which contain inflatable airbags to protect the hip. So far, these devices have been used mostly in nursing homes but will be available to purchase privately from mid-2023.

The products presented above are examples of each type of device available. Other similar devices can be purchased in the form of a wrist-worn device or an inflatable airbag. Furthermore, other applications can be downloaded onto phones for fall detection. At the time of writing, there are no known near-fall detection devices on the market.

2.3 Electronic Textiles

Electronic textiles (E-textiles) are an obvious choice for integrating a fall detection system as they are unobtrusive, comfortable, and hidden: These are desirable qualities for older people. Critically, comfort would be important to user compliance with wearing such a device for a prolonged period. To the knowledge of the author, textile-based fall detection systems do not currently exist. For this work, it is important to define an E-textile. In the literature the terms electronic textile and smart textile have been used interchangeably, however, there is a subtle distinction between the terms. An E-textile is a textile with integrated electronics and a smart textile has the ability to respond to external stimuli [43].

2.3.1 Electronic Textile Development

Although E-textiles have been referred to as a relatively new field of research, in reality, E-textiles have been around since 1883 [44]. There are three generations to the development of E-textiles. These generations are depicted below in Figure 2.1. The first generation of E-textiles was made by attaching rigid electronic devices onto a fabric surface [44,45]. The second generation of E-textiles was made by integrating the electronics at the fabric level such as knitted electrodes [45]. The third generation of E-textiles used functional fibres and yarns to create smart systems [44,45]. Embedding electronics into textiles has become more feasible due to the miniaturisation of electronic components and circuits [45–47].

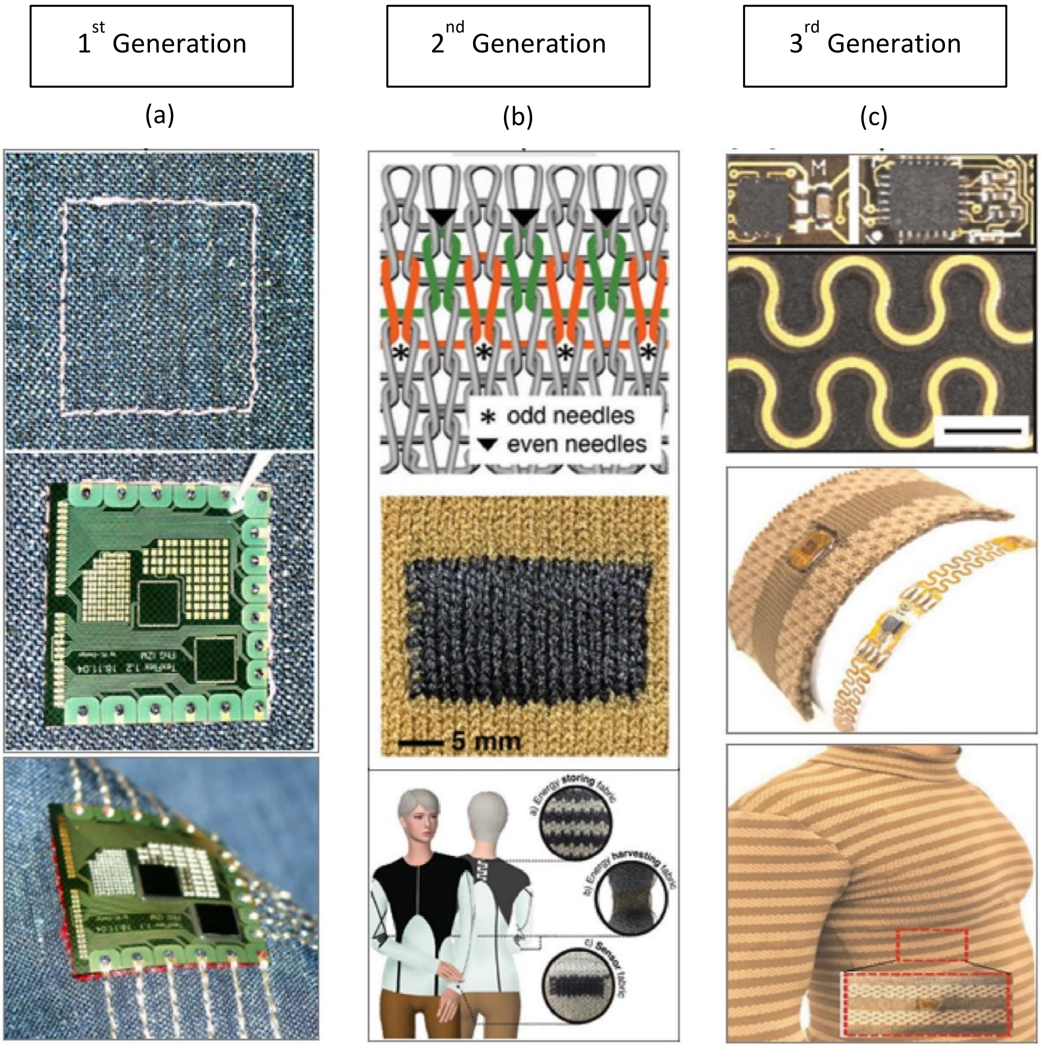

Figure 2.1 The three generations of E-textiles, reprinted with permission from ref [48] and is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). (a) Marking for the embroidery (top). The circuit placed onto the marker (middle) and the circuit embroidered through the contact pads (bottom). (b) Digital image of the knitted electrode (top), the actual image of the knitted fabric electrode (middle) and the concept art of the garment with the knitted electrodes (bottom). (c) Microscope image of the electronic strips (top), illustration of a woven electronic strip in a knitted fabric (middle) and an image to show how the strip can conform the wearer (bottom).

2.3.1.1 Commercially Available Electronic Textile Apparel

The most common E-textile is a heated blanket, but as the focus of this work is on wearables, below are examples of E-textile garments. Popular E-textile garments tend to be, either for function (heated garments) or aesthetics (light-up clothing).

Some examples of E-textiles are heated garments that can be used for leisure activities or even under workwear. These include vests, gloves, and leggings along with several other garments. Examples of companies that make and sell heated apparel are Nordic Heat [49], Bosch [50], Vulcan Sportswear [51], Regatta [52] and Keis Apparel [53].

For aesthetics, light-up clothing is fairly popular and can be bought from eBay, Etsy and Amazon. There are multiple companies that sell light-up apparel and two are discussed below. These include Illuminated Apparel [54], which creates clothing for both children and adults. The adult clothing contains t-shirts, jumpers, glasses and baseball caps. Another example of light-up apparel comes from Flash Wear [55]. They create clothing, shoes and accessories. Figure 2.2 shows an example of a light-up jumper from Next.

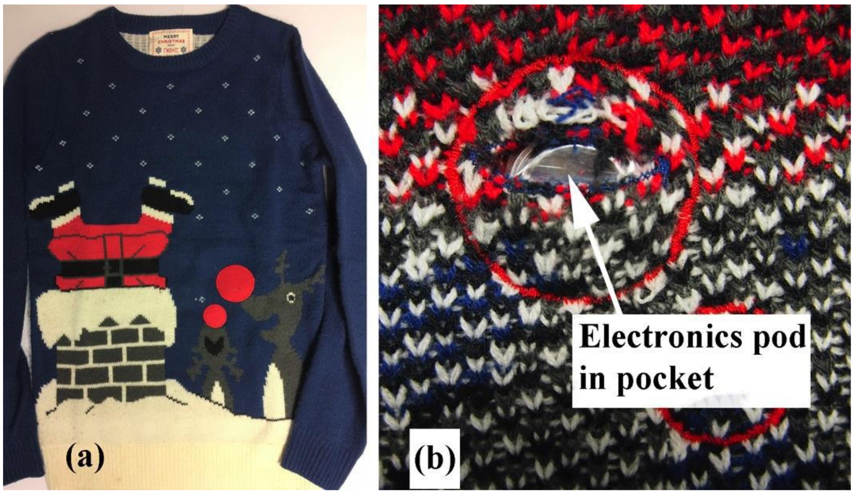

Figure 2.2(a) Image of a light-up Christmas jumper and (b) the close-up of the electronics pod that that contains the hardware. Reprinted with permission from ref [56]. Copyright Elsevier license no. 5627081215991

Along with these types of E-textiles, there are more expensive luxury items on the market. They are sensor-based products that can perform smart functions. The products discussed below are examples of luxury sensor-based E-textiles that are commercially available.

The Levi's commuter x Jacquard by Google trucker jacket (Figure 2.3) [57] connects to the user's phone via Bluetooth. It allows the user to control their phone (music, phone calls etc) by touching the cuff of the jacket. The cuff uses 'Jacquard' threads that were specially designed and manufactured by Google. They are made using conductive metal alloys blended with natural and synthetic fibres. The Jacquard snap tag provides haptic and light feedback to the user and is attached to the wrist.

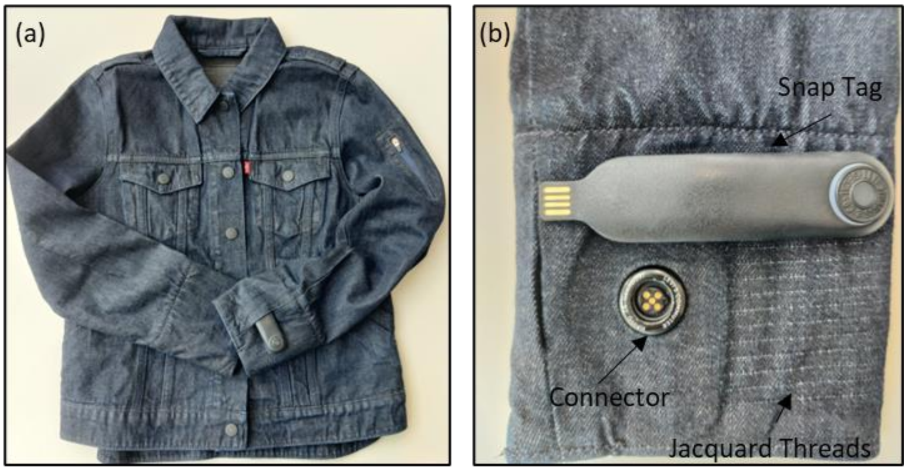

Figure 2.3 (a) Levi's x Google trucker jacket and (b) zoomed-in image of the interactive cuff to show the Jacquard Threads, the snap tag and the connector for the snap tag.

The Nadi X yoga pants by Wearable X [58] contain accelerometers and have the ability to give small vibrations via haptic actuators, using accelerometers and audio sensors to monitor posture. The user wears the yoga pants whilst performing a yoga routine and the sensors alert the user so they can adjust themselves if they are doing the yoga move incorrectly. The sensor technology is attached using a clip.

Similarly, the smart socks by Sensoria [59] require an attachable hardware module to function. The module can be used to count steps, track speed, distance, calories, cadence and foot landing. These smart socks can currently only be used with an iPhone.

The smart shirt by Hexoskin [60], like the other products described above, requires the use of an attachable device (sold separately) but also contains textile sensors. The shirt claims to measure physiological measurements such as heart rate, heart rate variability, breathing rate, breathing volume, activity (steps, cadence and calories) and sleep.

CuteCircuit [61] has created three types of garments. The Interactive Fashion section contains light-up clothing (t-shirts, dresses and running jackets) as well as a light-up handbag. The other two garments, HugShirt [62] and SoundShirt [63], both contain haptic actuators. The HugShirt can be used to send hugs over a long distance. The SoundShirt is a development of the HugShirt as it can also deliver hugs over a long distance. Furthermore, with the added haptic actuators it can allow deaf people to sense music and provide an immersive augmented and virtual reality.

The luxury products described above provide an overview of the types of E-textiles that are available commercially. All but the HugShirt and SoundShirt require the use of an attachable clip that contains the technology to make the garment smart. The HugShirt and SoundShirt claim to be made of only smart fabric. They do also claim to contain haptic actuators, Bluetooth 5 and the ability to be recharged. Currently, added Bluetooth and charging capabilities require the use of rigid technology. Therefore, their claims of no wires and smart fabric only, are confusing to the author. The website states that digital printing was used to define the haptic actuator areas. IMUs cannot currently be incorporated using printing technology. Therefore, alternative electronics integration techniques need to be explored.

2.3.2 Functional Fibres and Yarns

Functional fibres and yarn are used as they behave like normal yarns that can be woven or knitted into fabric.

There are commercially available functional fibres, such as the Radio-frequency identification (RFID) E-Thread technology produced by Primo 1D [64]. This E-Thread contains RFID chips that are connected and encapsulated to create a reel of E-Thread.

Within academia, an example of a functional fibre was developed at Massachusetts Institute of Technology, shown in Figure 2.4. It is fabricated using a thermal drawing approach [65]. This approach allows up to four solder pads to be connected. The study shows that temperature-sensing yarns and memory-storage yarns have been successfully created. It is also suggested that the temperature-sensing yarns, which are close to the skin within a t-shirt, can be used to track some motion; sitting, standing, walking and running based on subtle temperature changes. These yarns have been wash tested; however, this was done without laundry detergent, for 10 cycles and for 15 minutes only. As they do not clarify which standard they are using and it is not similar to ISO 6330, which is most commonly used [66], the results cannot be compared with other functional fibres and yarns.

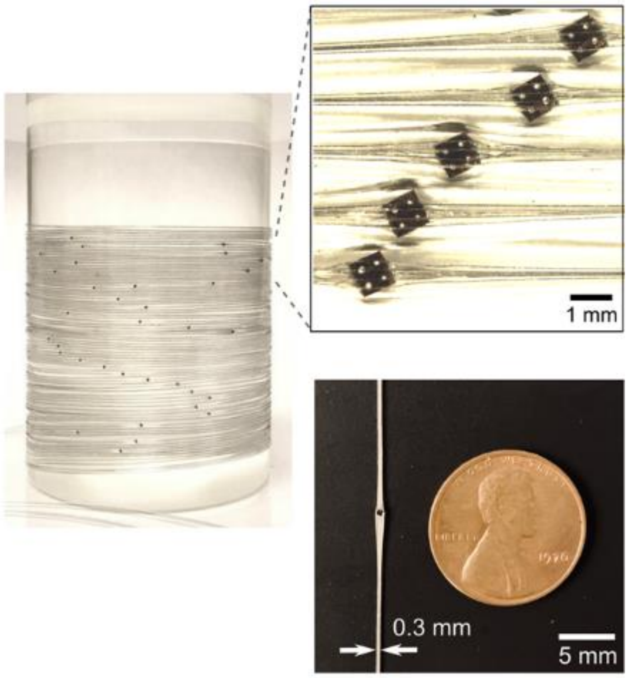

Figure 2.4 taken from this image [65]; is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). The image on the right shows a photograph of a spool of the functional fibred. The image on the top left shows is the functional fibre magnified. The image on the bottom the size of the fibre when compared to a coin.

2.3.2.1 ELECTRONIC YARNS

The Advanced Textile Research Group (ATRG) at Nottingham Trent University has successfully embedded sensors into yarn form to create electronic yarns (E-yarns) that can be woven or incorporated into knitted fabrics. The types of E-yarn that have been developed vary from LED E-yarns to more complex sensing E-yarns. The ATRG has created LED E-yarns that were tested on a costume used in performance [67]. This study successfully showed that the E-yarns can be incorporated into a stretch fabric without impairing the movement of the wearer. In addition, photodiodes [68], thermistors [69], acoustic sensors in the form of a MEMS microphone [70,71], and vibration sensors [71–73], have successfully been embedded into E-yarns. E-yarns are typically produced using the three-stage process described in Chapter 1 Section 1.3.

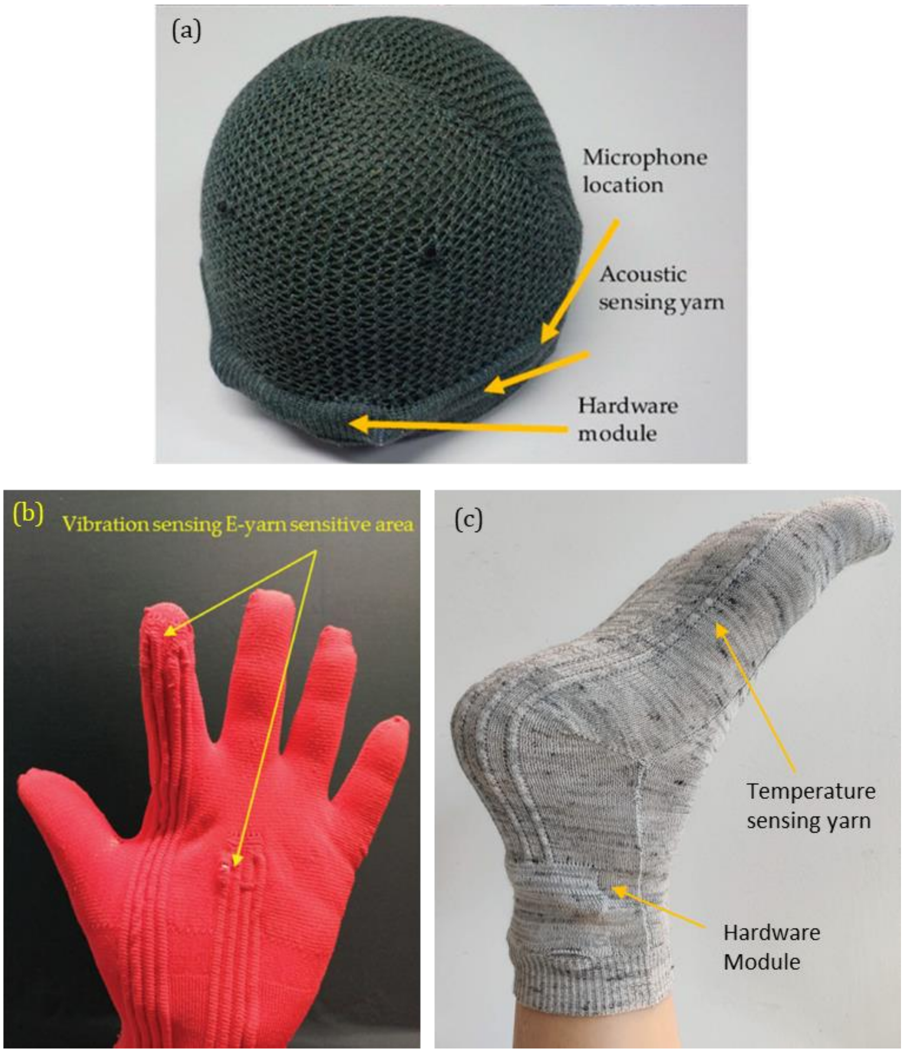

Figure 2.5 (a) Image of the rear of an acoustic sensing helmet cover, taken from [70]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). (b) Image of a vibration sensing glove, taken from [72]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). (c) Image of a temperature-sensing sock.

The advantage of E-yarns over other methods of integration is that they do not change the behaviour of the fabric that they are integrated into and that they are inconspicuous within the fabric. Critically, the E-yarns are comfortable to wear. Furthermore, the only limitation to the technology that can be produced comes from the size of the electronic components, which will continue to decrease as the electronics are developed.

The E-yarns have been shown to be machine washable, as demonstrated in a study conducted by the ATRG [74]. This study tested LED E-yarns, temperature-sensing E-yarns and acoustic-sensing E-yarns, as well as the conductive wires used in the E-yarns, for 25 machine washing and drying cycles based on ISO 6330 [75]. The results show that 100% of the conductive wire, 80 % of the LED E-yarns and the temperature sensing E-yarns survived washing and line drying. However, none of the acoustic sensing E-yarns functioned at the end of the washing and drying cycles. Additionally, only 20% of the LED E-yarns survived washing and tumble drying. The photodiode E-yarns were machine washed and tumbled dried only, and only 20% continued to function correctly [68]. All E-yarns were studied after they stopped functioning to diagnose the point of failure. The results showed that the conductive wire had broken strands, which altered the function of the E-yarns. Furthermore, the acoustic sensing yarn has the largest micropod, which may have led to failures sooner, as discussed in the wash testing article [74].

2.3.3 Electronic Textiles for Motion and Healthy Ageing

There are limited studies that have used electronic textiles for motion detection. Some of these use graphene-based sensors that can be attached to clothing to measure joint movement and respiration rate [76–78]. For a full textile-based sensor, the most common E-textiles used are strain or pressure sensors. There are not many studies that have been shown to use textile sensors for motion detection.

A textile capacitive pressure sensor was developed and had the ability to measure arm motion and muscle activity (biceps and triceps) [79]. Chen *et al*. [80] have developed a knitted sensor that can measure deformations including strain and pressure, and state that this can be used for human motion detection as well as pulse rate and other potential health monitoring. A stretchable fibre has been produced that can detect motion as it can respond to deformation of stretch, twist, bend and press simultaneously [81]. Yao *et al*. [82] have manufactured a sleeve to measure electrocardiogram (ECG) and motion. The strain sensor has the ability to measure motion and also has electrodes to measure ECG. The idea of measuring both ECG and motion together for well-being was also expressed in another study [83]. The definition of well-being is 'the state of feeling healthy and happy' according to the Cambridge Dictionary. Therefore, well-being and healthy ageing are intimately linked.

Within the literature, there is a comprehensive paper in 2019 that discusses the need for E-textiles and healthy ageing [84]. Importantly, the use of inertial sensors within E-textiles is mentioned for motion detection and its use in fall prevention and detection, but it clearly states that it has not been accomplished. Additionally, the paper highlights that the challenge that needs to be overcome is proper collaboration between the people who create the technology and the textile designers. The field would also benefit from more multidisciplinary work, i.e., material scientists, healthcare professionals and engineers.

Following the paper published in 2019 [84], there have been studies that have integrated inertial sensors within E-yarns. These include the vibration-sensing E-yarn that contains an accelerometer [72], which has also been used for gait classification [85]. The study on gait classification used a smart sock to reliably classify between different gaits. The smart sock was developed separately from this project and had no bearing on the development of this work.

In addition, one study [86] demonstrated an accelerometer connected to a small flexible strip circuit, that used Litz wire soldered onto pads on the circuit. The accelerometer and solder joints were encapsulated and directly woven into a sleeve. This sleeve was used to detect elbow and knee joint bending angles, as well as activity recognition between climbing stairs, walking and running. At the time of writing the author knows of no other inertial sensors integrated at yarn level or of any E-textiles that have been created for fall or near-fall detection.

2.4 HUMAN-CENTRED DESIGN FOR OLDER ADULTS

The definition of human-centred design (HCD) according to Ergonomics of Human-System Interaction - Part 210: Human-Centred Design for Interactive Systems (ISO 9241-210:2019) [87]

> *"…is an approach to interactive systems development that aims to make systems usable and useful by focusing on the users, their needs and requirements, and by applying human factors/ergonomics, and usability knowledge and techniques. This approach enhances effectiveness and efficiency, improves human well-being, user satisfaction, accessibility and sustainability; and counteracts possible adverse effects of use on human health, safety and performance."*

HCD stems from the fields of product design, engineering and computer science and focuses on the needs, wants and desires of the user [88]. It involves the intended users from the beginning of the process and Giacomin [88] states that:

> *"Human-centred design is thus distinct from many traditional design practices because the natural focus of the questions, insights and activities lies with the people for whom the product, system or service is intended,*

rather than in the designer's personal creative process or within the material and technological substrates of the artefact."

However, it is important to remember although there is a benefit in working with intended users when developing E-textiles there is the knowledge that only the designers and technologists have. Marc Steen [89] also considers this notion and says that "…*certain knowledge of certain people is privileged over other knowledge of other people*." To help with this, Steen recommends critical reflection during a project and to "…*combine and balance their own knowledge and ideas with users' knowledge and ideas; they will have to decide when and how, and to what extent, to be human-centred."*

For this literature, there is a focus on HCD for older adults which is centred around health technologies, smart textiles and textiles. When searching for HCD that involves older adults there are papers on methodologies and technology more generally, which is discussed in section 2.4.1. To the knowledge of the author, there is no literature on HCD in the fields of fall and near-fall detection. In addition, within the field of E-textiles, there is limited research using HCD and there is an awareness of the need for research that involves intended users. This was discussed during the annual E-textiles conference that was held at Nottingham Trent University in November 2022. Within the literature, there is a discussion on the benefits of working with intended users to gain their perceived needs for the development of E-textiles and wearable technology [90]. Another study was conducted that investigated the views of people aged 60 and over on health, healthy ageing, healthcare devices, smart healthcare devices and attitudes to smart textiles. The main conclusion was that to develop E-textiles for healthy ageing, there is a need to use an HCD approach [91]. Section 2.4.2 focuses on designing textiles for older adults and one of the studies presented is a smart textile although the article is centred on the design rather than the technology.

There is one project that is often referenced when discussing designing assistive technology for older adults. This project named MATUROLIFE [92,93] was a large EU Horizon project that ran from 2018-2021, involved nine countries in Europe and was awarded € 5 050 370.75 [94]. The methodological approach of this project was codesign. Co-design (also known as co-creation) is a form of HCD that allows the users or participants to be co-creators with the designers and other experts [89]. Co-design allows the participant to be involved from the conception of the technology [89]. Initially, they conducted semi-structured interviews to plan the subsequent workshops. Two workshops were held, the first was an exploration and the other was for the co-design of the products. The exploration workshops were used to continue to gain insight into the priorities of the older adults and resulted in the three types of products to develop. The priorities for older adults found were temperature regulation, improving balance and reducing falls, and improving sleep and mobility. The co-design workshop was used to inform the design of the products using the needs and desires given by the older adults along with the designers and the researchers. A smart shirt for temperature regulation, smart shoes for balance and falls and a smart sofa for improved sleep and mobility. The initial interviews looked at older adults' views on clothing, footwear and furniture with the intention of developing a prototype in each of those categories. This was a successful project that used specific technology to develop the E-textiles. The technology is not described in depth. In the future, it would be beneficial to find the concerns of older adults and then determine what type of technology is appropriate for their needs.

2.4.1 Technology

Due to the origins of HCD, there is a lot of research on human-computer interaction (HCI), which is linked with technology acceptance. For older adults, the main considerations for accepting technology it cost, privacy, perceived need, ease of use and obtrusiveness [95,96]. A study conducted by Kin *et al.* was completed to find the difference in how older vs. young adults adopt the use of activity trackers. The study has shown that the ease of learning was the greatest factor affecting the adoption of the technology [97]. This is useful for any research that requires older adults to adopt new technology as it must be easy and simple. It has also been found that a lack of information on what older adults want from wearable technology [98]. These two points show the need for HCD when designing technology. This has been discussed and methodologies have been proposed that consider older adults [99–102].

2.4.2 Textiles

Likewise, Imbesi *et al.* [103] have established a methodology specifically for designing smart garments for older adults. This methodology has shown that HCD is useful in understanding older adults and can be used to elicit a positive perception of smart textiles. This methodology can be used to evaluate different design solutions by a multidisciplinary team.

One article showcased the use of co-design to develop sportswear for active ageing [104]. This case study focused on the textile rather than the technology. They found that older adults want more subtle styles and clean lines as well as age-appropriate colours. Age-appropriate was used for colours as well as a flattering design. Older adults are not interested in fast fashion and dislike inconsistent sizing. They would prefer more sizes of one style over lots of different styles. During the project, it was clear that there was distrust for synthetic fibres, which tends to come from a lack of understanding. As the project progressed, their minds were changed as they learnt more about textiles and fibres. Lastly, they would like to use their smartphones as the hub for the technology and would like the garment to be washed easily.

The case study above involved both older men and women. However, this thesis is focused on women as they have more non-fatal falls than men [105,106]. In addition, women tend to be discounted when designing a gender-neutral device [106]. Furthermore, designing for women as they age is incredibly complex [107]. There is always an issue around finding age-appropriate yet flattering clothing. This is echoed in a study conducted to look at designing womenswear more effectively to meet the physical and emotional needs of older women [108]. This study found that older women are aware of fashion, but they need their body features to be considered to ensure proper sizing and fit [108]. This study also highlights the importance of using an HCD approach to ensure that the needs of the people you are designing for are taken into consideration.

2.5 Conclusions

From the fall and near-fall detection studies, it is clear that the best choice of sensor is a six-axis IMU with a combination of an accelerometer and gyroscope. This will also show if either an accelerometer or gyroscope would be sufficient, this will be shown in the data collected to find the optimal sensor placement, which will be discussed in Chapter 3. However, from the fall and near-fall detection studies and commercial devices, it is unclear where the placement of the sensor should be or the sampling rate that should be used. These vary which has led to the following placements to be tested: wrist, chest, waist, lower back, thigh and ankle. The head has not been chosen as the author finds it to be an awkward placement and undesirable when designing E-textiles. Along with finding the optimal placement, a few sampling rates need to be tested to find which is appropriate for near-fall detection. The following sampling rates chosen include 25 Hz, 50 Hz and 100 Hz, as no clear optimal sampling rate could be determined by the literature. The methods used to determine the sampling rate and sensor position can be used by other researchers.

In addition, the fall and near-fall detection studies presented in section 2.2 focus very heavily on analysing the data using different methods, most notably some form of machine learning.

The sensors appear to be chosen at random and the hardware used is not always disclosed but when it is, it tends to be commercially available microcontrollers. There is no evidence that any consideration has been put into the design of the devices.

Furthermore, no information within the literature has been found asking people what they would like a fall detection system to look or feel like. The idea of using inflatable airbags has been presented as well as a commercial airbag device. However, as this research is focused on healthy ageing, and prevention before a fall occurs, this does not seem suitable. Moreover, within the E-textiles community, the lack of collaboration between different disciplines has been mentioned. It is important to design E-textiles that people will want to wear. It is the view of the author that the end users should be consulted when creating a system that is optional for them to wear.

Designing for older adults, whether it be technology, textiles or E-textiles, is not easy. Researchers need to consider what the older adults want, how they will accept technology as well as the fit and feel of the textiles. Therefore, it is necessary to use HCD to be able to create technology and textiles that people actually want. Otherwise, it will be difficult to get them to accept it.

This literature review has shown that the gaps this thesis will fill are a thorough investigation of sensor placement along with the sampling rate and sensor itself required. Developing an IMU E-yarn and an E-textile for fall or near-fall detection by using an HCD approach. Using the HCD approach for E-textiles generally is uncommon. As discussed above, to the knowledge of the author, there are no studies in the field of fall and near-fall detection that have used HCD when developing the technology. Finally, there are currently no fall-detection E-textiles nor has an IMU E-yarn or E-textile previously been developed.

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CHAPTER 3. OPTIMAL PLACEMENT OF AN INERTIAL SENSOR FOR FALL AND NEAR-FALL DETECTION

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The work presented in this chapter was presented in the Sheldon Group conference. A conference proceeding was published after the conference, which presents a small part of this work [1]. The author list of the article is **Zahra Rahemtulla,** Theodore Hughes-Riley, Jake Kaner and Tilak Dias.

The experimental work was conceived and conducted by Zahra Rahemtulla with Dr Theodore Hughes-Riley providing input and supervising. The data collection, organisation, visual analysis, and data interpretation was conducted by Zahra Rahemtulla.

Prof Jake Kaner and Prof Tilak Dias provided supervision.

3.1 INTRODUCTION

In 2020, the world's percentage of over 65s was 9.3% which is predicted to increase to 16% by 2050 [2]. As a result, healthy ageing is vital for ensuring a good quality of life for the older population. Falls are a major concern for the over 65s age group. The consequences of falls are physical injury [3], deterioration in mental health [4] or mortality [5]. Falls are costly to health care systems globally. For instance, in the Republic of Finland, the average cost to health care systems is US$ 3611 per fall [6].

The ability to detect falls in real time could reduce the probability of serious injury and loss of confidence, resulting in the possible prevention of future falls [7]. Consequently, the use of wearable technology for monitoring falls could decrease pressure on health care systems. Currently the commercial products available for automatic fall detection come in the form of watches [8,9], pendants [10,11] and panic buttons [12,13], as discussed in Chapter 2. Additionally, it is unclear as to how accurate/reliable these products are.

Although one of the objectives of this thesis was to find the optimal placement of the sensor for near-fall detection, initially it was important to find the optimal placements to accurately detect a fall to ensure good classification between falls and activities of daily living ADLs. This was critical to define the overall design of the E-textile. Near-falls are harder to detect, as they are more subtle than a fall. Therefore, this initial classification of correct positioning for the sensor informed later experimental work to identify near-falls.

While there have been a significant number of studies exploring fall and near-fall detection, the placement of the sensors is often not explained, and typically only one sensing location is used. Literature has shown sensors positioned at the chest [14–16] at the back of the neck [17], anterior superior iliac spine (pelvis area) [18] wrist [18,19] and waist [20,21]. To the knowledge of the author, only one limited study has explored the optimal position of the sensor [22]: This study focused on finding the optimal sensor placement using machine learning. Full experimental details were not presented in the paper, so it is unclear how they have attached the sensors to the body. Additionally, in the literature referenced above each sensor used is different and they use varying sampling rates which is not explained. As discussed in Chapter 2, this thesis has not focused on developing a machine learning algorithm and is more focused on the creation of a garment that users want to wear for near-fall detection.

Therefore, this pilot study was performed to try to find optimal sensor location for fall, and potentially near-falls as well as the sampling rate required. There is no complete study that has tried to find optimal sensor location, sampling rate and classification for ADLs and falls, which is what the study has done. Based on the literature various activities were chosen for the participants to perform, to simulate activities of daily living (ADLs) that could look like falling as well as a fall itself. The results of this pilot study were used to determine whether falls and ADLs can be distinguished from one another. It also identified the most appropriate sampling rate, as well as three potential sensor placements for prototype development. This information was used to decide that near-falls can be detected and further investigation needed.

3.2 Methods and Materials

3.2.1 Participants

For the pilot study five healthy female volunteers, aged between 22-31 were used. Their heights ranged from 1.57 m to 1.72 m and their weights ranged from 50 kg to 98 kg. Ethical approval was provided from the Nottingham Trent University Schools of Art and Design, Architecture, Design and Humanities Research Ethics Committee. Informed consent was provided by all the participants before the study. All the participants were female, as women are more likely to have non-fatal falls [6]. Each participant was asked to perform 10 activities: walking, walking slowly, kneeling, reaching high and low, sitting on a chair, sitting on a stool, lying down, 'Timed Up and Go', 'Turn 180^0' and a controlled sideways fall onto a crash mat. These activities were chosen as they mimic ADLs. The 'Timed Up and Go' and 'Turn 180^0' tests were included as they are used by clinicians for fall risk assessments [15].

3.2.2 Sensor Arrangement

Six sensor locations were chosen based on the literature for fall and near-fall detection [24–26], which included: waist, chest, lower back, thigh, ankle, and wrist. This can be seen in Figure 3.5. A commercial motion tracker was used for the user trials. This product was called a MetaTracker and was bought from MbientLab (MbientLab, 848 Girard St, San Francisco, CA). The MetaTracker was chosen as the associated software unit (MetaHub) that allows multiple MetaTrackers to be monitored simultaneously. The experiments required all six of the trackers to be put on at once so that the data between them could be compared directly. The MetaTrackers were connected to the MetaHub via Bluetooth, provided by MbientLab, to set the data acquisition parameters and log the data. The inertial measurement unit (IMU) within the MetaTracker was the Bosch BMI160 (BMI160, Bosch Sensortec, GmbH, Gerhard-Kindler-Strasse 9, 72770 Reutlingen, Germany), which contains a 3-axis accelerometer and 3-axis gyroscope.

In addition, a Bosch BMI160 Shuttle board and associated Application board (v2.0) was used for validation experiments. These are connected to a laptop using very long ethernet cable and controlled using the PC based software (Desktop Development), that allows the user to set the data acquisition parameters and log the data.

3.2.3 Activities

The ten activities are split into four sub-sections, which are also used in Section 3.3. The experiments were performed in the Nottingham Trent University city campus gym. Figure 3.1 is an image of the room used along with the equipment used.

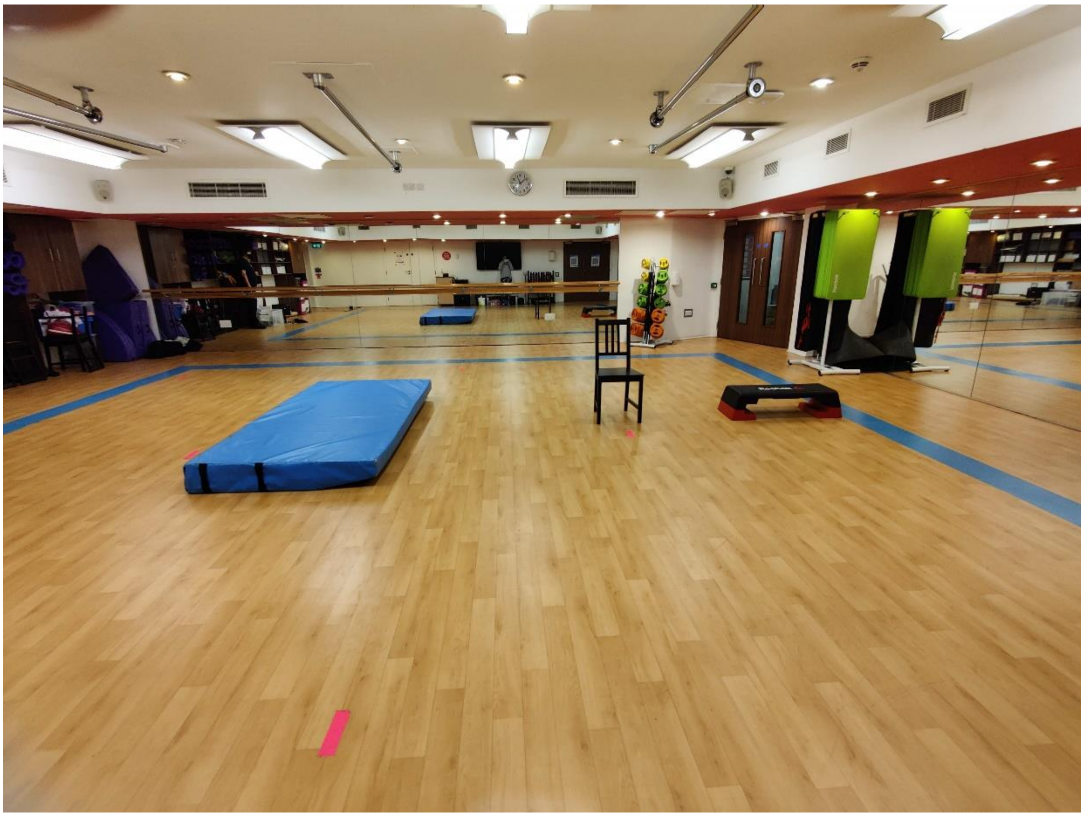

Figure 3.1: Experimental set-up for the user trials.

3.2.3.1 Walking

There were two different walking activities, walking and walking slowly. These were done to see if there was a notable difference in the data between the speeds that people walk. For both walking and walking slowly, the participants went at their own pace but walked the same distance for both. The data showed the turns that the participants made walking from one side of the room to the other.

3.2.3.2 Sitting ADLs

The three sitting ADLs were sitting on a chair, sitting on a stool, and kneeling. These activities have been grouped together as sitting on a chair and stool are essentially the same movement, with the exception being that there was a longer range of movement to sit on the stool. Kneeling is in the same section as sitting on a chair and sitting on a stool as the action is different, but the results show a comparable pattern. Figure 3.2 is an image of a participant during the kneeling activity. All of these movements required the participant to start the activity standing, perform the sitting ADL, stay in that position and return to standing.

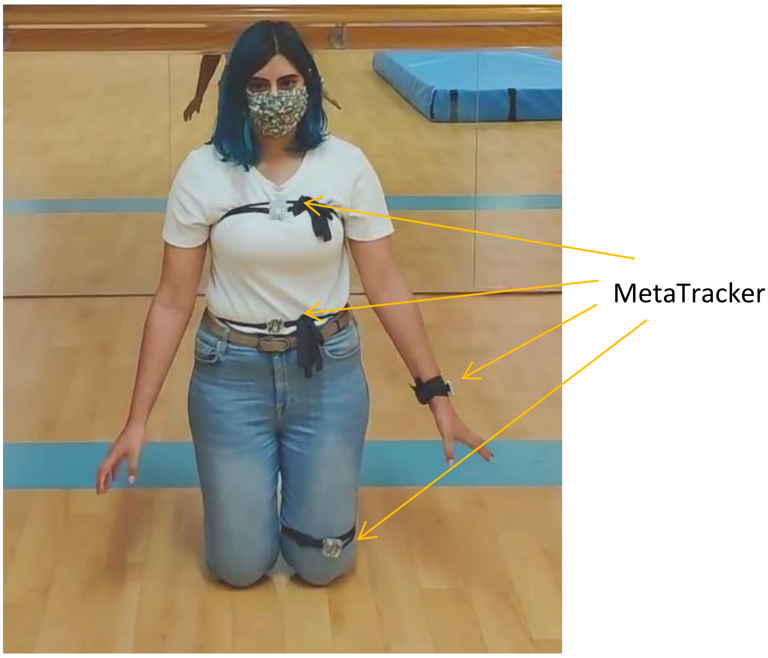

Figure 3.2: Kneeling activity

3.2.3.3 Other ADLs

The rest of the ADLs are shown in the same section for ease. These include, reaching high to low, 'Turn 180^0' and 'Timed Up and Go' test. For reaching high to low, the participant reached up with their left hand, and then bent down to touch the floor with the left hand. Figure 3.3 is an image that shows a participant reaching high to low. The 'Timed Up and Go' test required the participant to start seated on a chair, they then got up and walked to the end of the room, turned, and returned to the chair to sit back down.

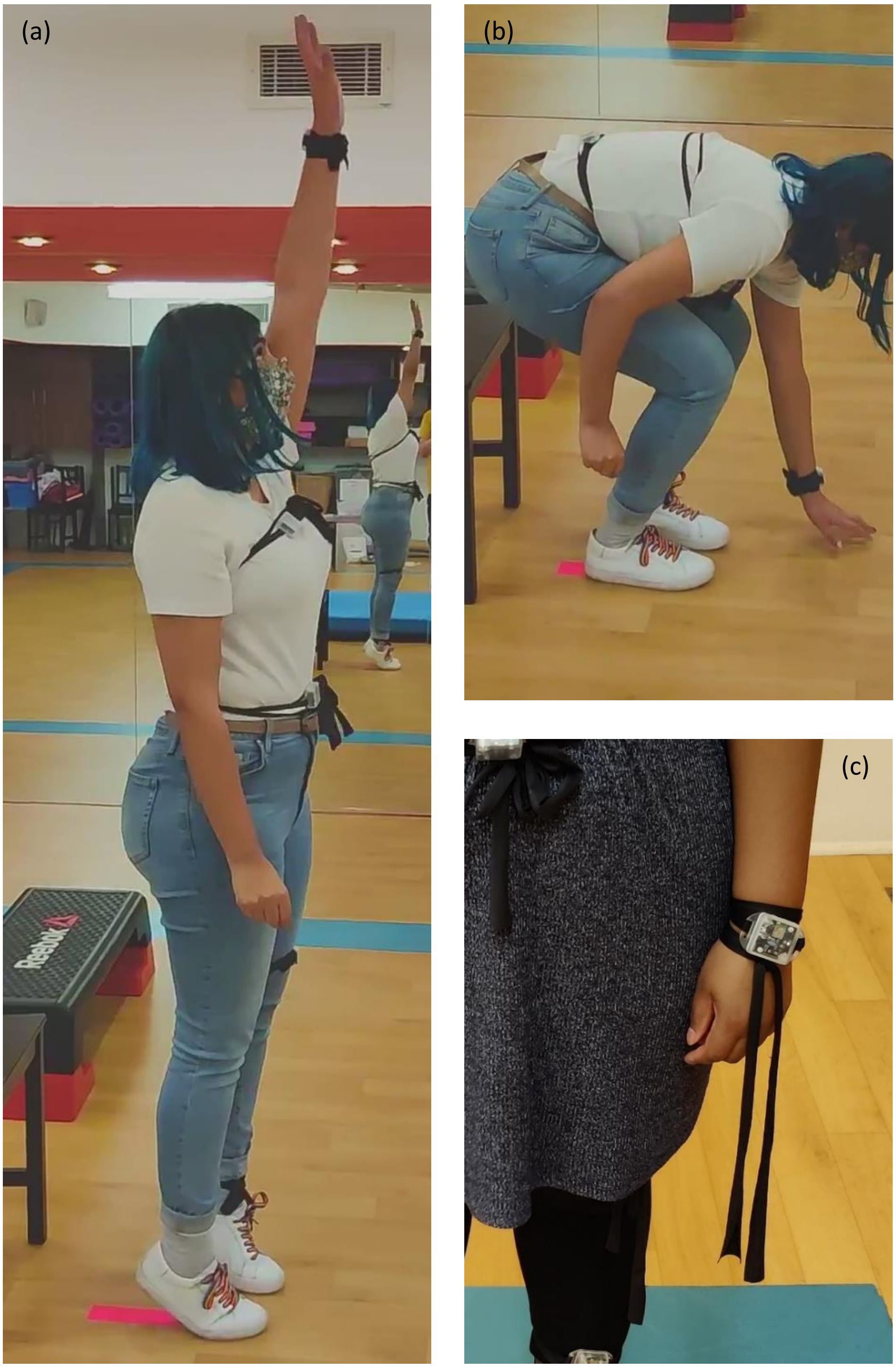

Figure 3.3: Images of the reaching high to low activity, as well as a close-up of the MetaTracker attached to the wrist. (a) Reaching high and (b) reaching low. (c) Close-up of the MetaTracker attached to the wrist.

3.2.3.4 Lying Down and Falling

Lying down and falling both involved the use of a crash mat. The participants were asked to lie on the crash mat. All participants chose to lie on their back. They were also asked to fall onto the crash mat sideways. Figure 3.4 presents an image of a participant falling onto the crash mat.

Figure 3.4: Image showing a participant falling sideways onto a crash mat

3.2.4 User Trials

The first set of experiments were completed using all five volunteers performing all of the activities. Six MetaTracker were used in each location simultaneously for the experiments to allow for a direct comparison. The MetaTrackers were controlled using the MetaHub from MbientLab. A 25Hz sample rate was used for the accelerometer and the gyroscope in the sensor and the software collected and saved the data. The intention was to use different sampling rates to collect the data. However, as the MetaHub did not always work correctly, only 25Hz was used. The data was processed in Microsoft Excel (Microsoft Corporation, Redmond, WA, USA) by creating a pivot table to average together three data points logged at each time interval. The was done as the sampling rate was not accurate and there were three data points at each timestamp. The pivot tables were then used to create graphs to visually represent the accelerometer and gyroscope data. The MetaTrackers where attached to the body using strip of fabric and tightly tied to the body. Figure 3.5 shows an image of the sensors attach to the body.

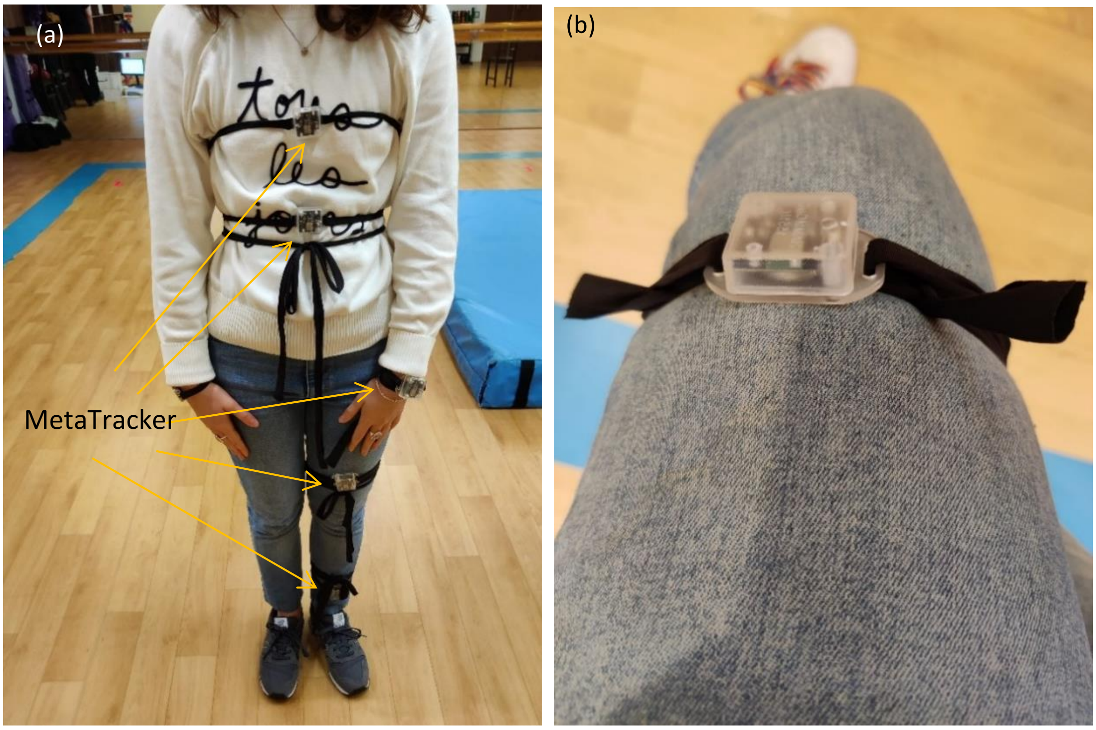

Figure 3.5 (a) Image showing five of the MetaTrackers attached to a participant (b) Zoomed in image of the MetaTracker attached to the thigh.

3.2.5 Validation Trials

When graphing the data from the first set of experiments it became apparent that the MetaTracker sampling rate was not accurate, and that there were gaps in the datasets at certain time intervals. While the data was still useful, it was important to validate the data collected, and a second set of experiments were performed using one participant, five activities and one MetaTracker at a time in three of the locations of interest. The activities included: walking, kneeling, reaching high and low, lying down and 'Timed Up and Go'. The locations of the MetaTracker used were the waist, thigh, and ankle. Unlike in the user trials, this set of experiments used one MetaTracker at time rather than all three simultaneously. Additionally, at the thigh, the Bosch application board was used along with the MetaTracker. Three sampling rates were used, 25 Hz, 50 Hz and 100 Hz to find the limitations of the MbientLab system, confirm the suitability of the sampling rate used, and as a comparison to the Bosch application board and software. The Bosch application board was used for the final set of validation experiments to see whether the behaviour of the sensor was altered by the MetaTracker circuit. Figure 3.6 is an image of the Bosch application board attached to the thigh at the same time at the MetaTracker.

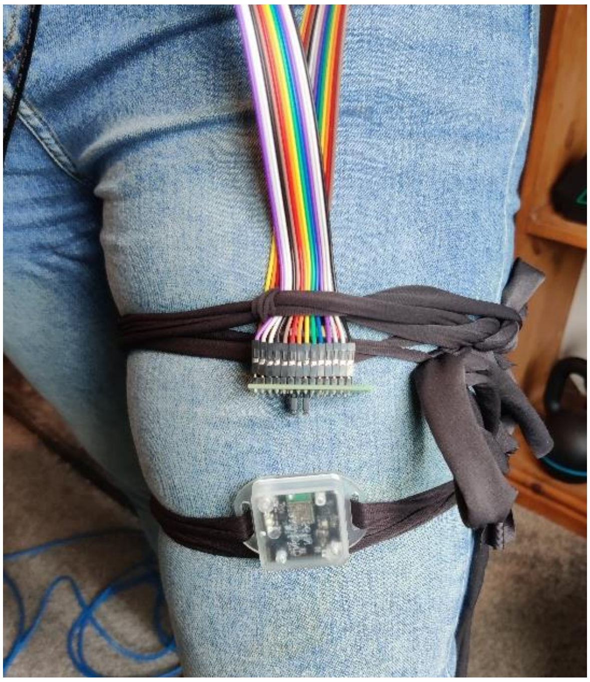

Figure 3.6: Image of the Bosch application board attached to the thigh along with the MetaTracker.

3.3 RESULTS

The results presented below show the User Trial data for one participant. This is because as stated in Section 3.2.5 the data collected did not have an accurate sampling method. Therefore, the only way to analyse this was visually. Sections 3.3.13.3.4 show the acceleration and angular velocity data for one participant at all six locations. Each section is categorised by sensor location and further sub-categorised by the activity. For all the data, x y and z have different orientations based on how the tracker was attached to the body. This was hard to avoid as there was no marking on the tracker to ensure each one was put on in the same direction. There are random peaks and troughs in the data presented below that come from issues with the MetaTracker. As there are 60 graphs for just one participant, some of the other participant data has been presented in Appendix A.3 Other Participant Data. All the other participant data has not been presented as it is in alignment with participant one. The validation data that was taken has been presented in Appendix A.4 Validation Trials, as it aligns with the data presented below. All of the raw data can be found on Figshare [27].

3.3.1 Thigh

3.3.1.1 Walking

Figure 3.7 presents data from the thigh of one participant when walking. The corresponding data for when the participant walked slowly is shown in Figure 3.8.

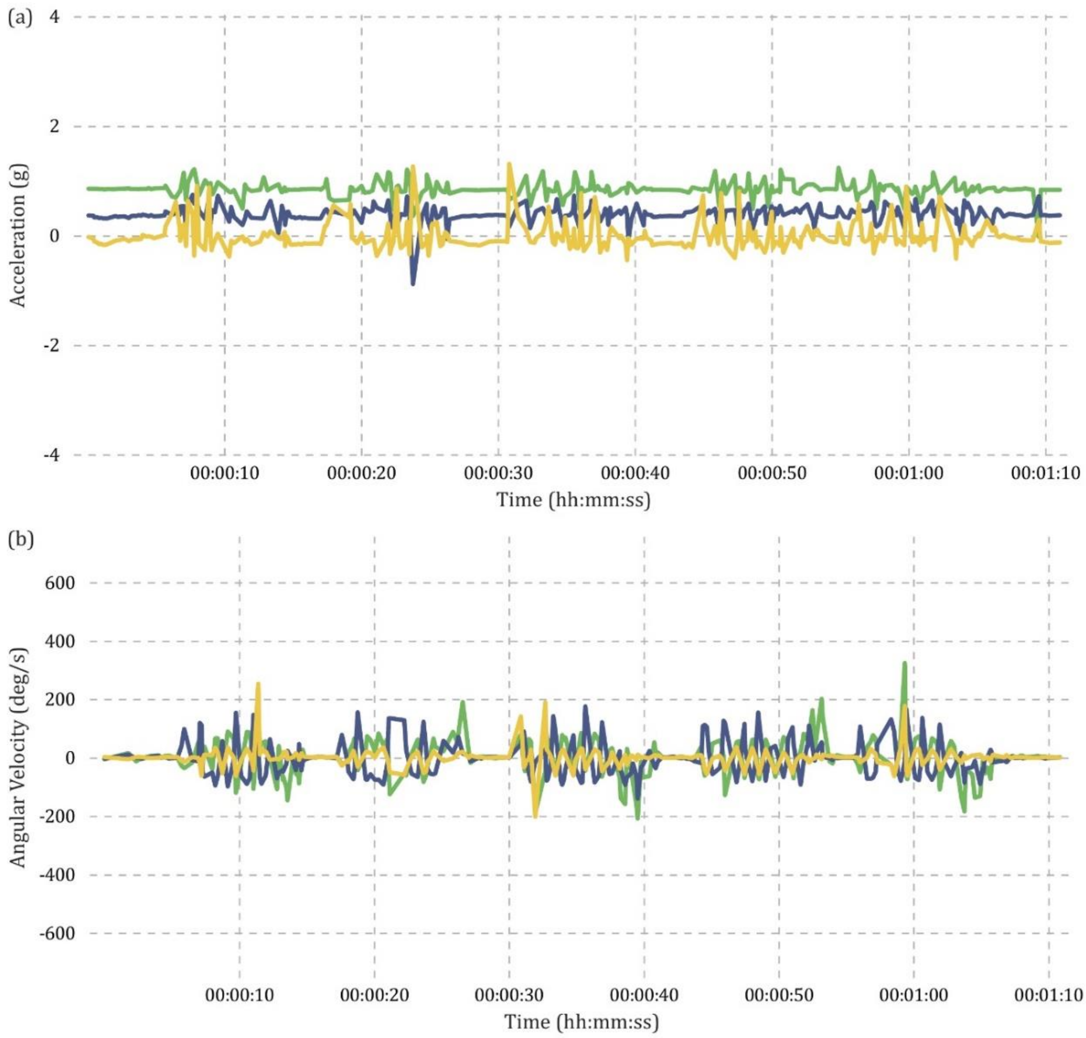

Figure 3.7 Data taken at the thigh for the walking activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

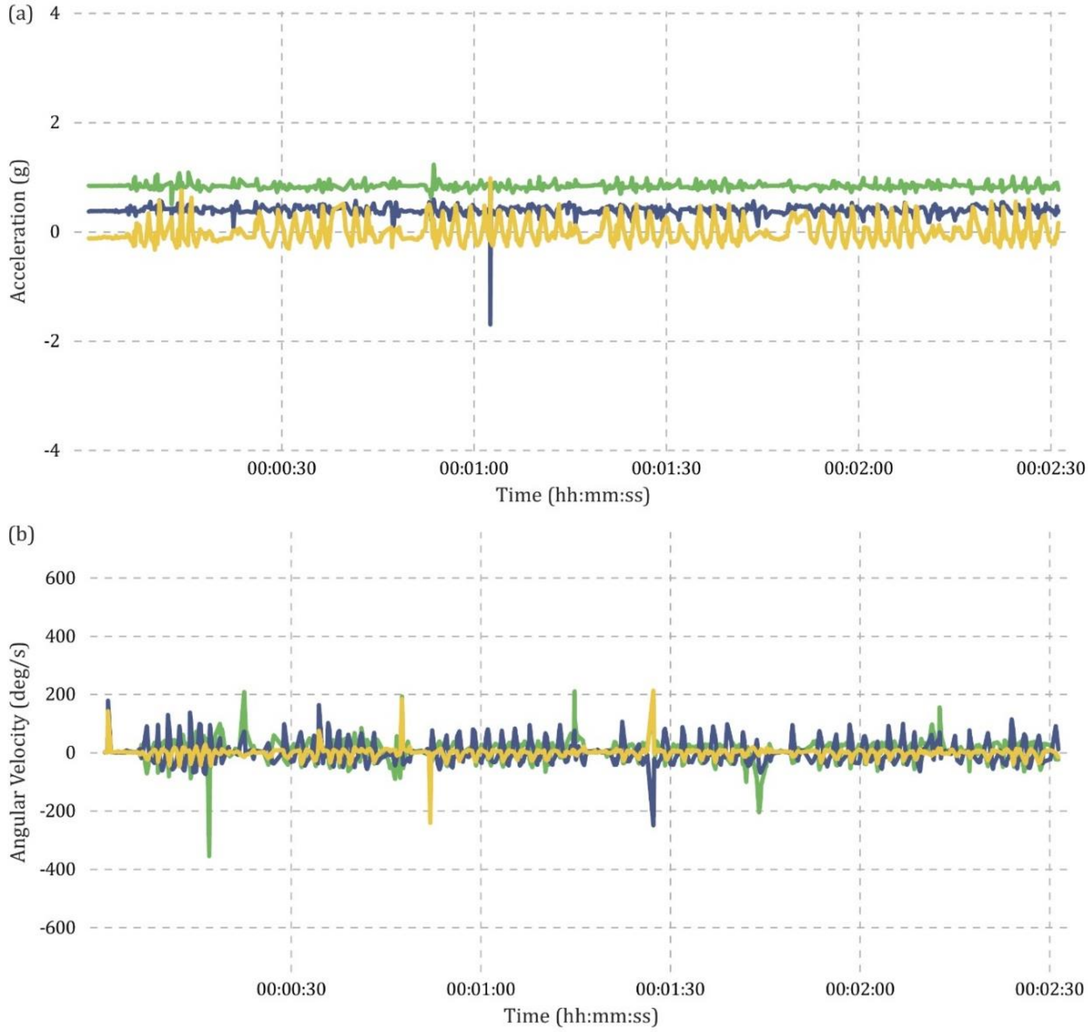

Figure 3.8 Data taken at the thigh for the walking slowly activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Data from both walking and walking slowly showed similar patterns, as would be expected. Figure 3.7 and Figure 3.8 show five clear repeats of the activities (this is most clear in Figure 3.9b, where the pause between the activities is visible) in both the acceleration and angular data. The data matched closely with the video recordings of the activities being conducted. In Figure 3.7a, it was harder to differentiate between the 4th and 5th repeats of the walking activity: This was due to the leg movement and the time between the repeats being smaller than the other ones, due to a shorter pause between the repeats (confirmed by the video).

3.3.1.2 SITTING ADLS

As described in Section 3.2.3.2, sitting ADLS include sitting on a chair, sitting on a stool, and kneeling. These are grouped as they are similar activities. They started with the participant standing, the action and finally the participant returned to standing.

Figure 3.9 presents data from the thigh for one participant when sitting down and then standing up from a chair.

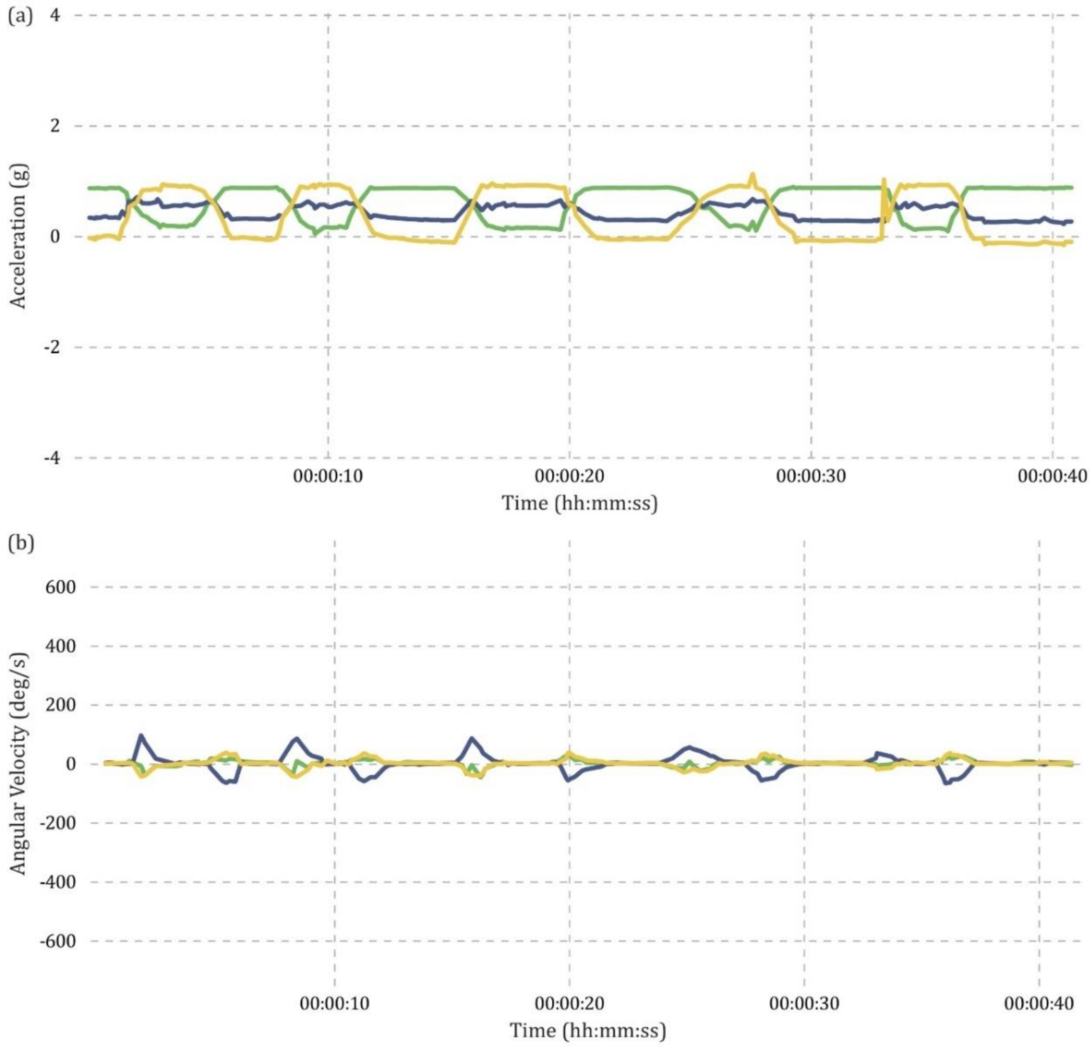

Figure 3.9 Data taken at the thigh for the sitting on a chair activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.10 presents data from the thigh for one participant when sitting down and then standing up from a stool.

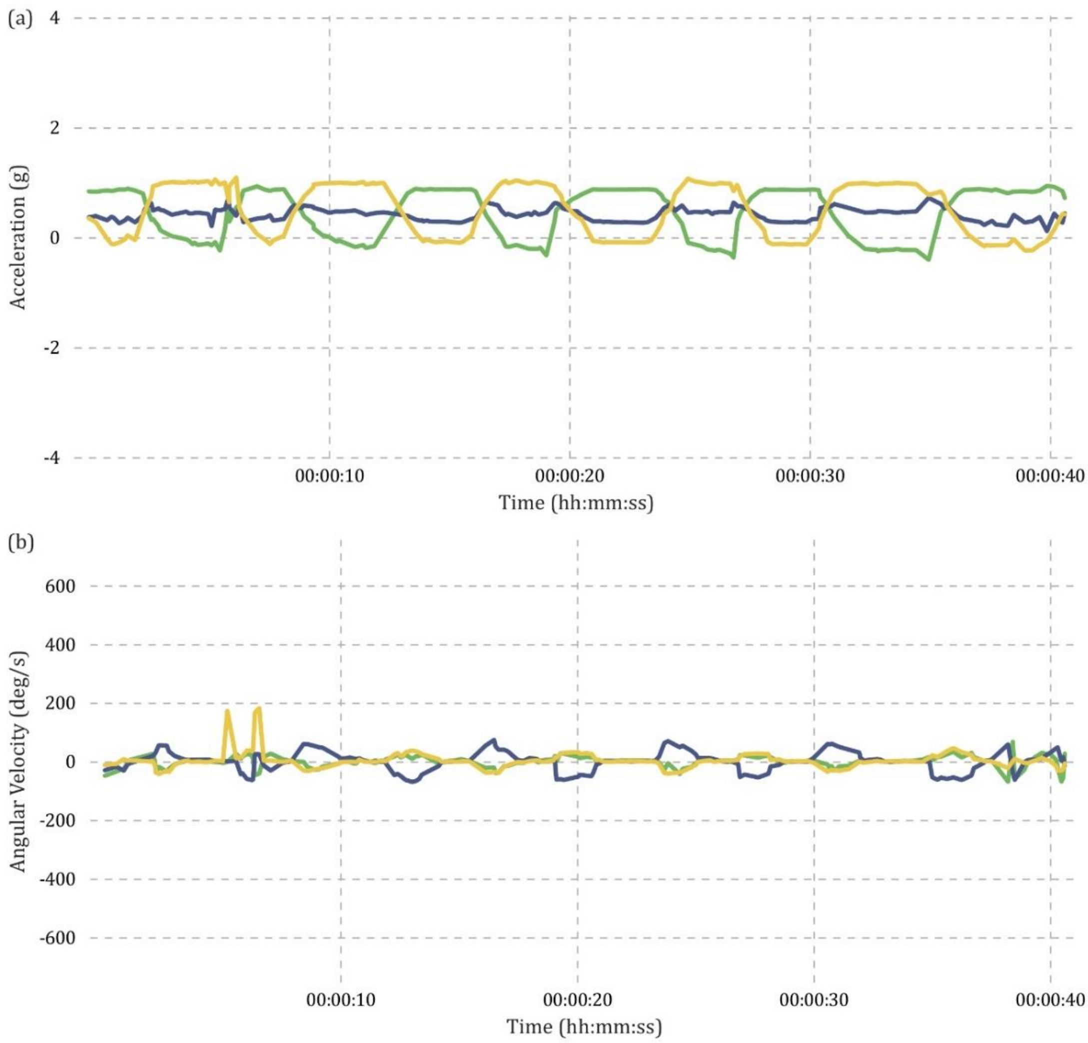

Figure 3.10 Data taken at the thigh for the sitting on a stool activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

In Figure 3.9 and Figure 3.10, there are clear patterns in both the acceleration and angular velocity data corresponding to when the participant stands and sits. In both cases, it is clear from the acceleration data when the participant is sitting as there is a decrease in the x-axis and an increase in the z-axis and y-axis. When sitting on the chair the increase in z-axis acceleration is equivalent to the decrease in the x-axis. The increase in the y-axis is much smaller than the increase in the z-axis. As the participant returns to standing, the acceleration in each axis is reversed.

When sitting on a stool, the pattern for acceleration is the same as for sitting on a chair. The main difference is that there is a larger change in the x-axis value as the participant sits.

The gyroscope data shows an increase in the y-axis and a decrease in the x-axis and z-axis as the participant is sitting. The decrease in the x-axis and z-axis is about half the increase in the y-axis. As the participant is standing the angular velocity in each axis is the opposite to sitting, as would be expected.

The acceleration and change in angle correspond with the sitting and standing actions observed in the video.

Figure 3.11 shows the participant kneeling, staying still on their knees and then standing back up.

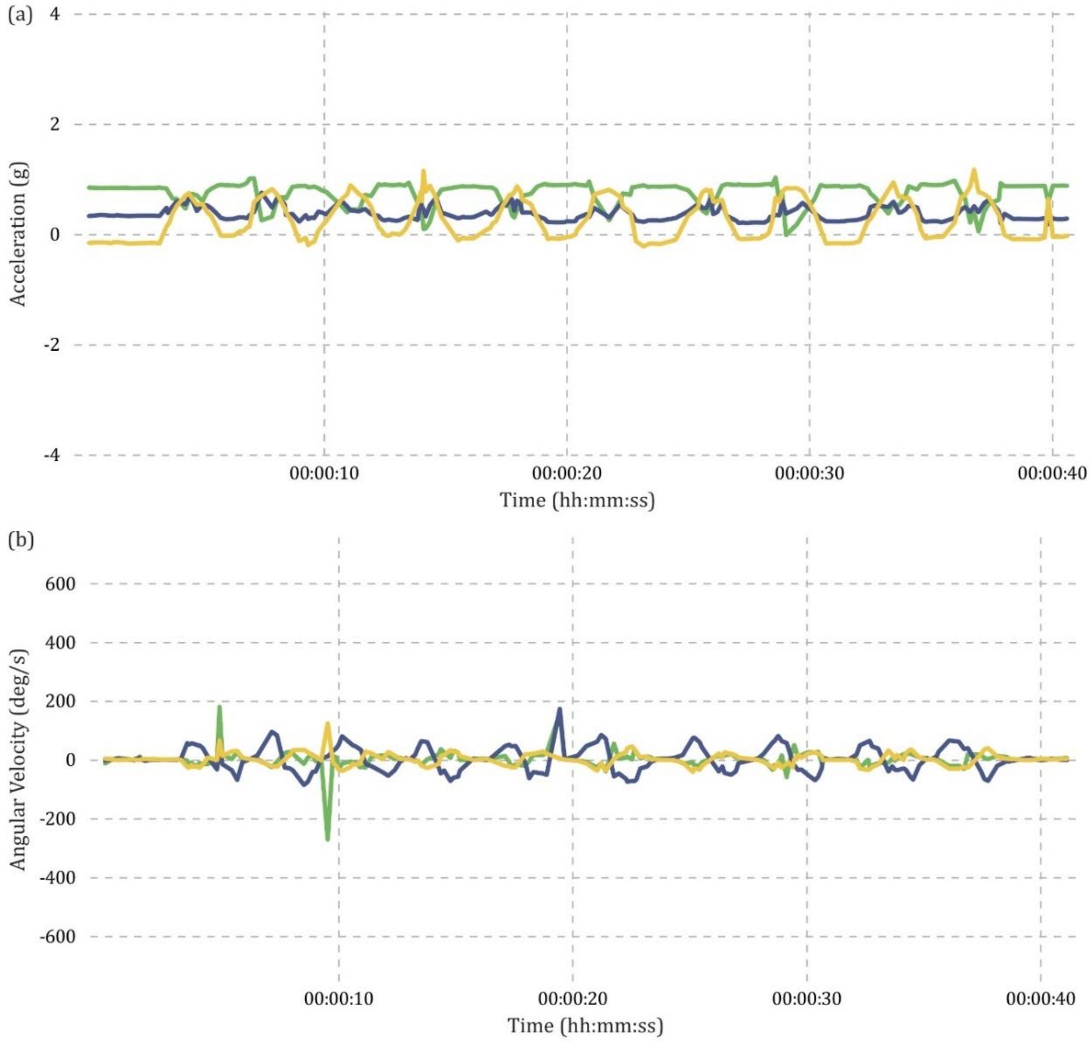

Figure 3.11 Data taken at the thigh for the kneeling activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The action of kneeling can be seen in the acceleration data as a decrease in the x-axis and y-axis and an increase in the z-axis. As the participant stays still on their knees, the acceleration data looks the same as when they are standing still, as they are not moving. As the participant stands back up, there is a decrease in the x-axis and y-axis and an increase in the z-axis.

The gyroscope data shows an increase then a decrease in the y-axis and a decrease then an increase in the x -axis and z-axis as the participant is kneeling. This is similar to the data in Figure 3.9b as the participant is sitting and standing. As the participant is standing back up the data follows the same pattern as kneeling, an increase then a decrease in the y-axis and a decrease then an increase in the x-axis and z-axis.

The actions observed in the video correspond to the data presented in the graphs.

3.3.1.3 OTHER ADLS

This section describes other ADLs: Reaching high to low, 'Turn 180^0' and 'Timed Up and Go' test.

Figure 3.12 presents data from the thigh when one participant is reaching high to low. During the activity, the participant reached up with their left hand and then bent down to touch the ground before returning to stand.

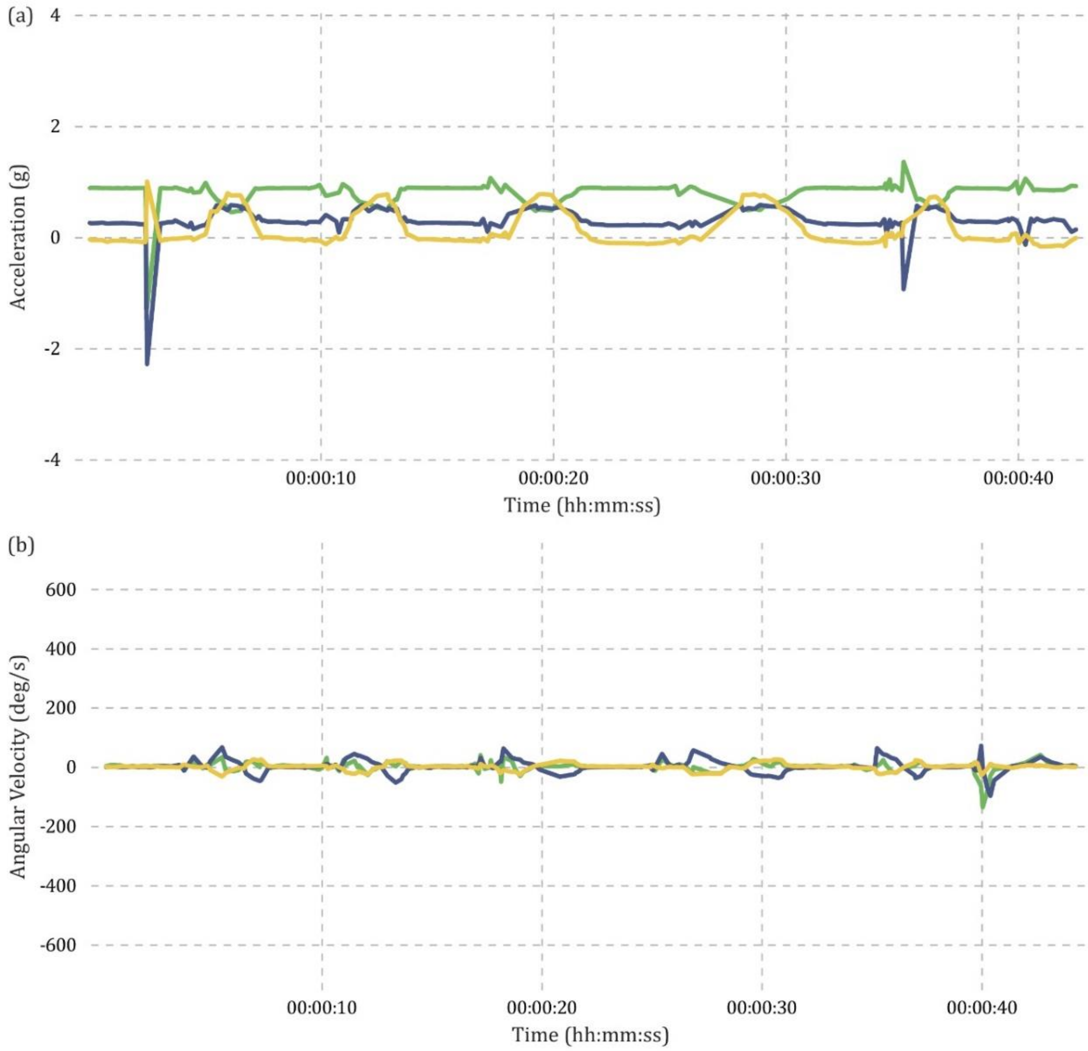

Figure 3.12 Data taken at the thigh for the reaching high to low activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

In Figure 3.12a the acceleration data shows the same pattern as in Figure 3.11a. The angular velocity in Figure 3.12b shows the same pattern that is seen in Figure 3.9b and Figure 3.11b, an increase then a decrease in the y-axis and a decrease then an increase in the x-axis and z-axis. This is because the tracker on the thigh can only detect the participant reaching low and it is more like kneeling. It should be noted that the change in the angular velocity for reaching high to low was less than for kneeling. It would be extremely different to distinguish between kneeling and reaching high to low using the data collected at the thigh. In addition, reaching high is only detected by the wrist which is seen in Figure 3.62 in Section 3.3.4.3.

Figure 3.13 presents data from the thigh when one participant is turning 180^0.

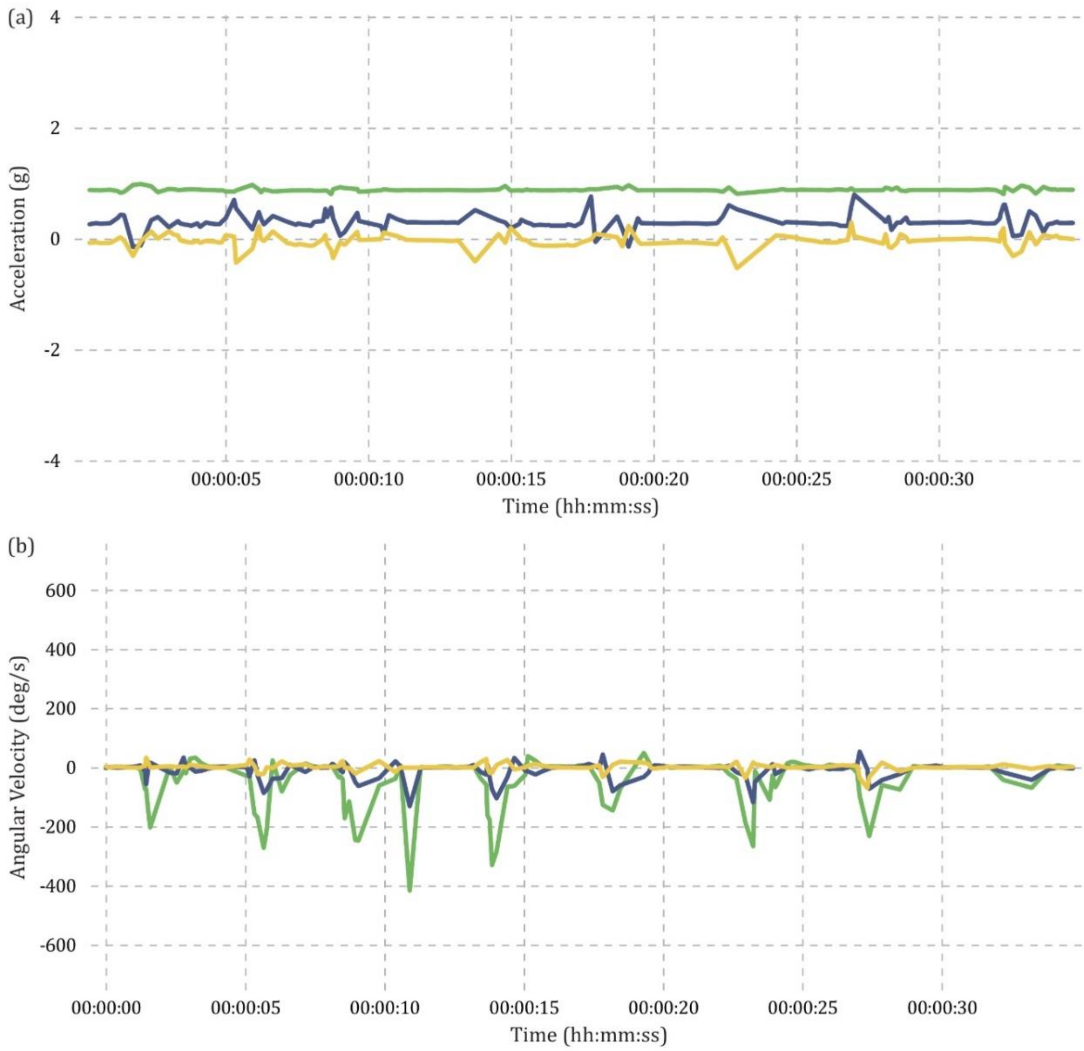

Figure 3.13 Data taken at the thigh for the turning activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.13 shows 8 turns, which are most visible from the gyroscope data in Figure 3.8b and corresponds to the video. For each turn, there is a large decrease in the x-axis (up to -417deg/s) and a smaller decrease in the y-axis and z-axis. In the gyroscope data, there are two large decreases during the third turn. Each of the turns was in the same direction. In the acceleration data in Figure 3.13a, there are 8 points of movement, therefore the two large decreases that are seen in the graph one after the other are one turn only. For each turn there is a decrease in the z-axis and either an increase or decrease in the y-axis. In the x-axis, there is only a slight increase at each turn point that is visible.

Figure 3.14 shows data from the 'Timed Up and Go' test. This is a combination of walking, sitting on a chair and turning activities.

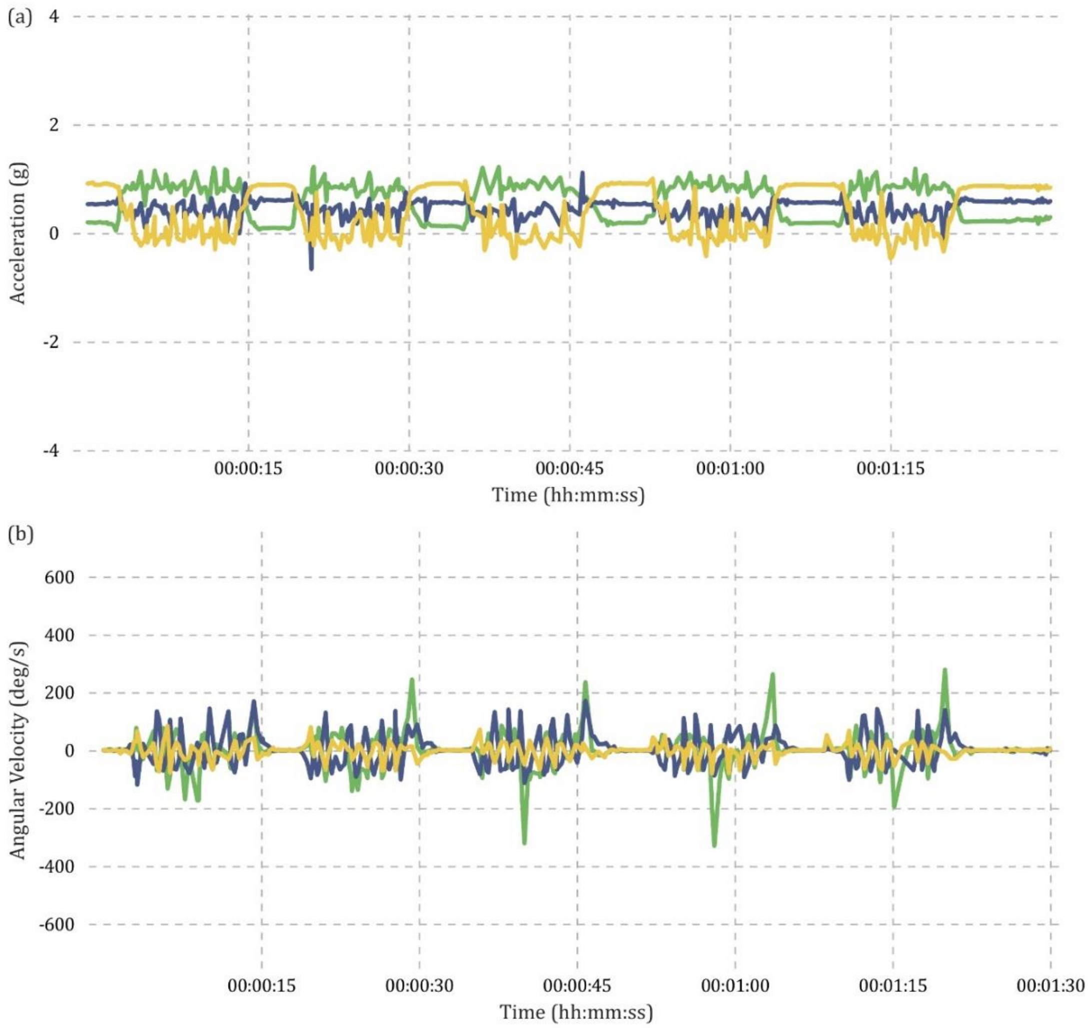

Figure 3.14 Data taken at the thigh for the 'Timed Up and Go' test. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.14a shows the same pattern as observed in Figure 3.9a, where there is a decrease in the z-axis and y-axis and an increase in the x-axis as the participant stands and the reverse as the participant sits back down.

The complex sequence of movements makes it hard to clearly distinguish a pattern within the gyroscope data, mostly due to the walking activity. There is a decrease in the y-axis as the participant stands and a small increase in the x-axis and z-axis as seen in Figure 3.9b. In the middle of the walking activity there is a large decrease in the second turn in the x-axis angular velocity (230deg/s) which indicates the turn and towards the end of the test there is another turn as the participants sit back down, shown by a large increase in the x-axis in the opposite direction. This is because the participant has turned in the opposite direction and is clearest to see in the third repeat. This corresponds to the video. As the participant sits back down, there is an increase in the z-axis and y-axis as well as a decrease in the x-axis as seen in Figure 3.9b.

3.3.1.4 Lying Down and Falling

Figure 3.15 shows the participant starting from a standing position to lying down flat on their back and returning to a standing position.

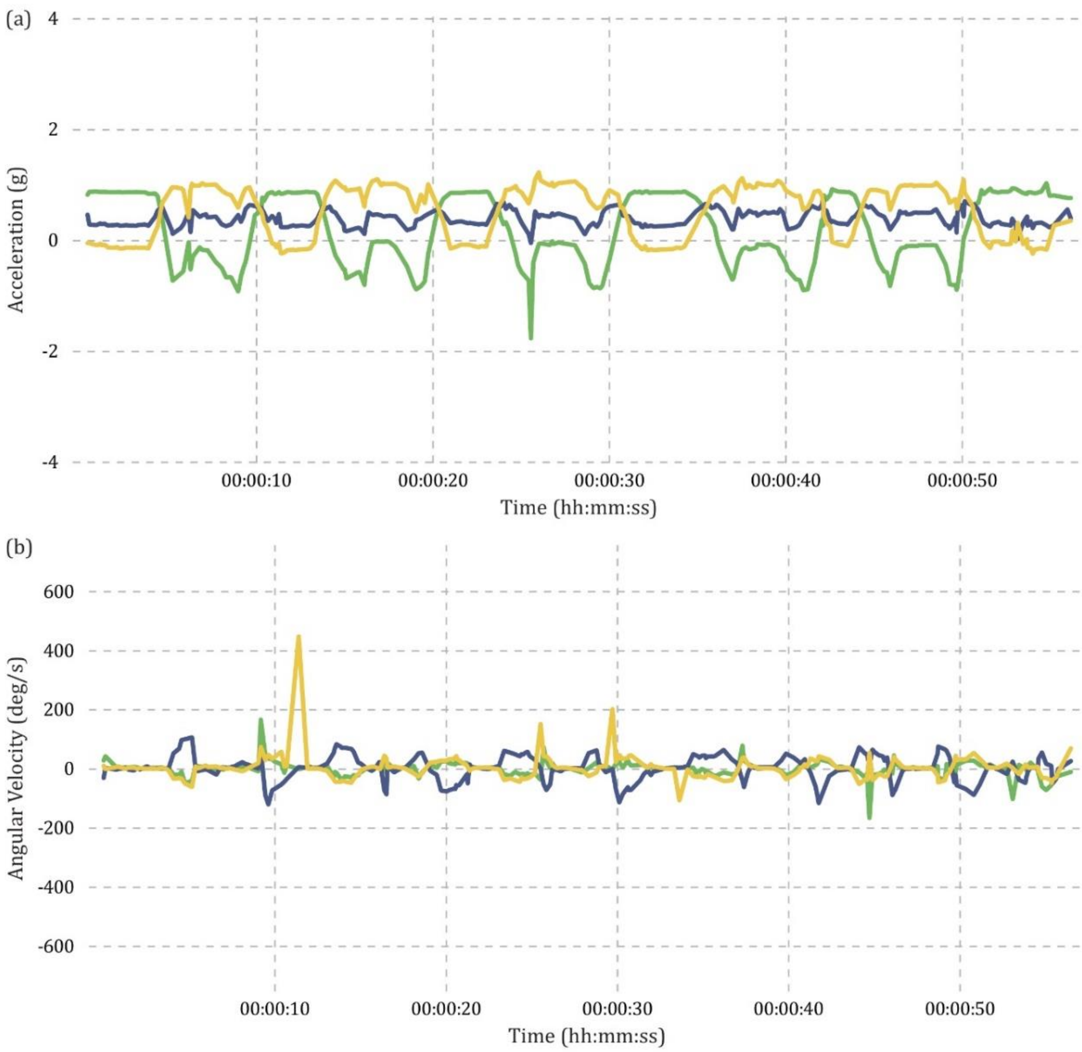

Figure 3.15 Data taken at the thigh for the lying down activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The pattern observed in the acceleration data is similar to the sitting ADLs there is a large decrease in the x-axis (1.58g) and a small decrease in the y-axis (0.17g) as well as a large increase in the z-axis (1.06g) as the participant is lying down when looking at the first repeat. As the participant is lying there is no change in the x, y and z-axes, but as they start to rise there is an increase in the x-axis and y-axis and a decrease in the z-axis back to the standing position. There is some movement in all three of the axes, which comes from thigh movement as the legs are straightened out for lying down fully and recoiled to get up again.

The angular velocity shows a similar pattern also seen in the sitting ADLs in Figure 3.11b. There is an increase in the y-axis and a decrease in the x-axis and z-axis as the participant lies down and the opposite as the participant straightened the legs out. As the participant recoils their legs and returns to standing the same pattern is repeated, an increase in the y-axis and a decrease in the x-axis and z-axis followed by the reverse as they are standing. As the participant is lying or standing still there is no movement detected.

The actions observed in the video correspond to the data presented in the graphs.

Figure 3.16 shows the data from the thigh for the fall sideways onto a crashmat. The participant falls, then stays lying down before returning to stand.

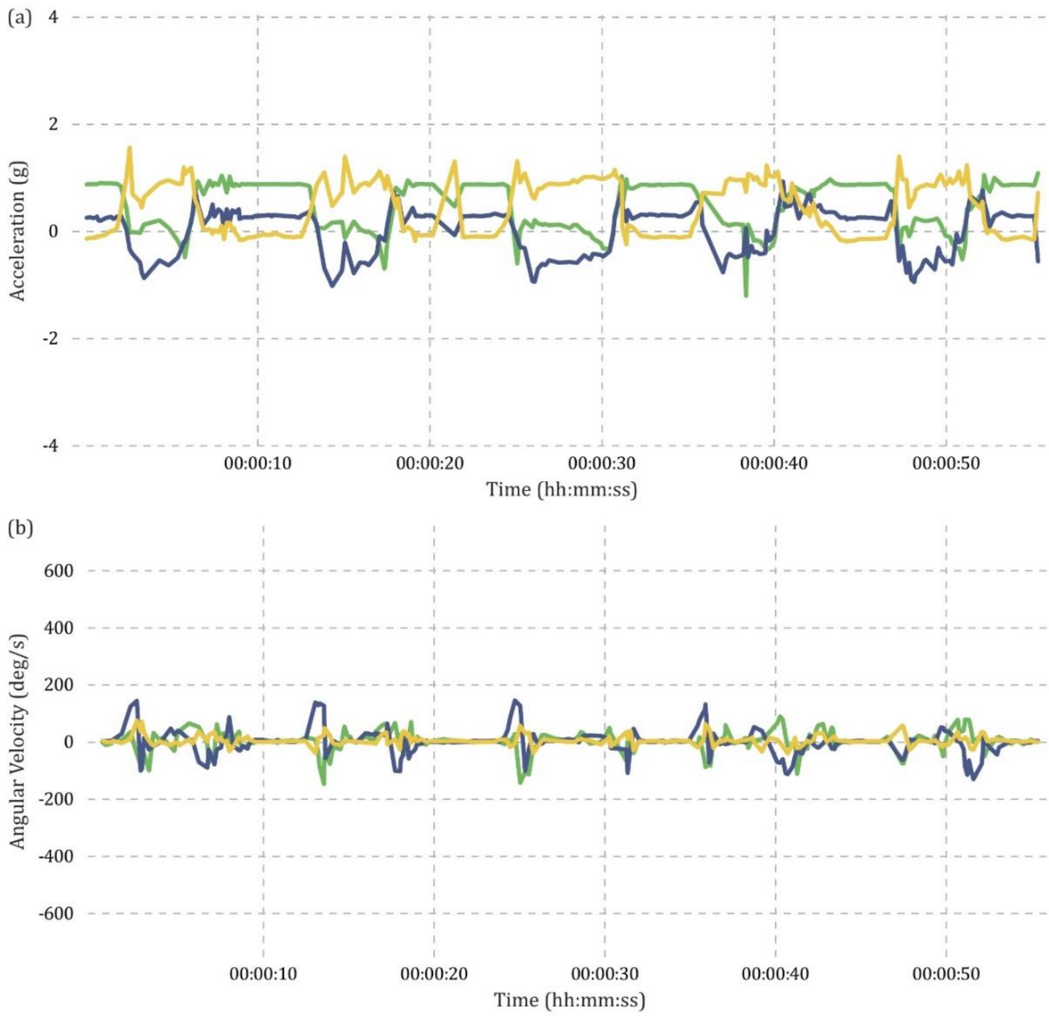

Figure 3.16 Data taken at the thigh for the fall. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The fall activity was similar to lying down but was performed sideways on the mat and there was less movement in the legs once the participant was laying on the mat. However, there is leg movement comparable to the lying down activity to get back up.

Figure 3.11a is similar to sitting ADLs and lying down. However, there was a larger increase in the z-axis and a larger decrease in the y-axis compared to the other activities given the rapidity of the motion. There is also a decrease in the x-axis which does not appear to be significantly different to the other activities.

In the gyroscope data, there was an increase at the point of falling (confirmed by the video) in the y-axis that is much larger compared to the other activities (1.04 compared to 0.11 for laying down, when looking at the first repeats), again due to the rapid nature of the fall.

There is an increase then decrease in the angular velocity for all three axes as the fall occurs and the opposite as the participant stands again.

3.3.1.5 SUMMARY

The thigh walking, turning, lying down and falls can all easily be distinguished from each other. However, sitting on a chair and sitting on a stool is very similar and might be difficult to distinguish from one another. Additionally, kneeling and reaching high to low also have similar patterns that are difficult to distinguish between.

3.3.2 CHEST, WAIST, AND LOWER BACK (CENTRE OF GRAVITY)

The data below presents readings taken at the chest, waist and lower back as these sensors were all located near the centre of the body (and thus the participant's centre of gravity) and show similar results. All the sensors were orientated differently but the patterns, explaining the differences were seen in the actual axis that data was recorded in.

3.3.2.1 WALKING

Figure 3.17 and Figure 3.20 shows the data collected at the chest for walking and walking slowly respectively. Figure 3.18 and Figure 3.21 present the data from the waist for walking and walking slowly respectively. Figure 3.19 and Figure 3.22 display the data from the lower back for walking and walking slowly respectively.

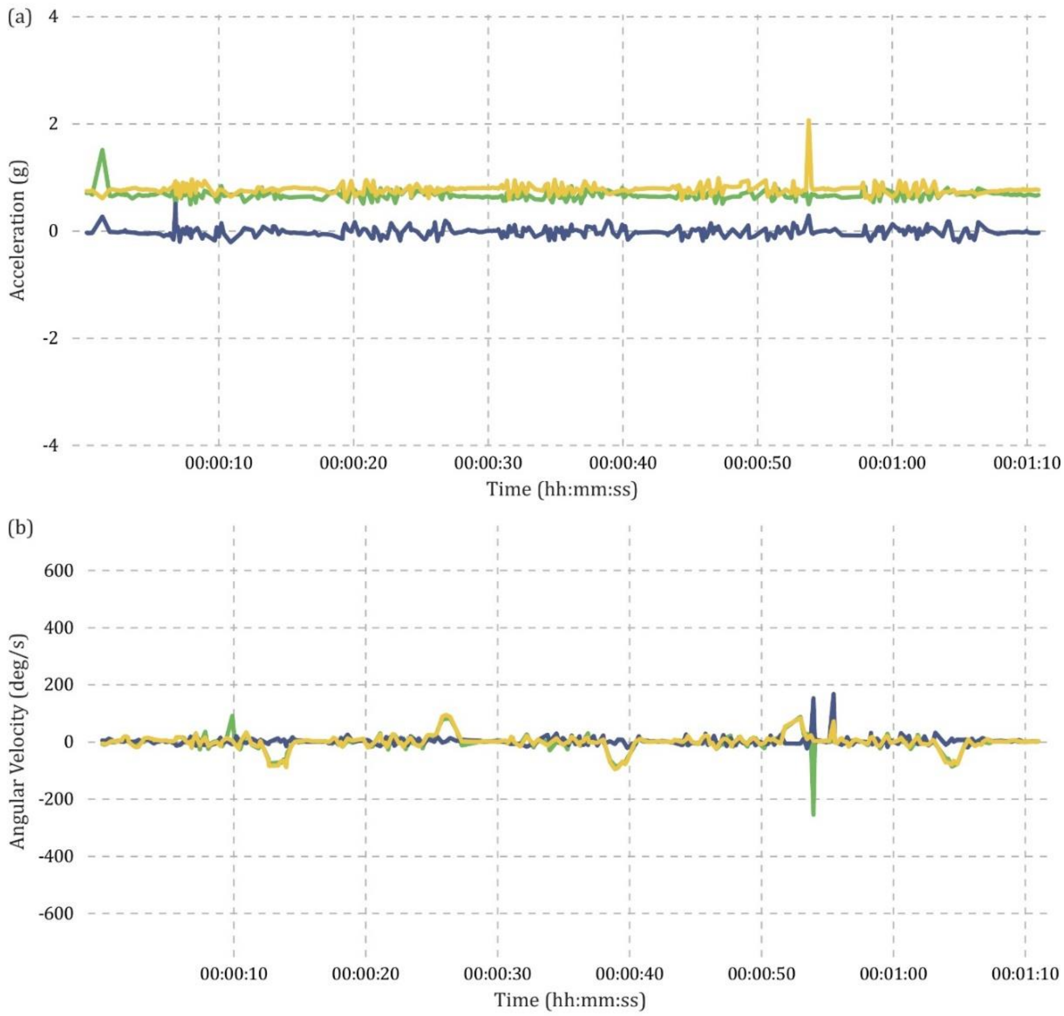

Figure 3.17 Data taken at the chest for the walking activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

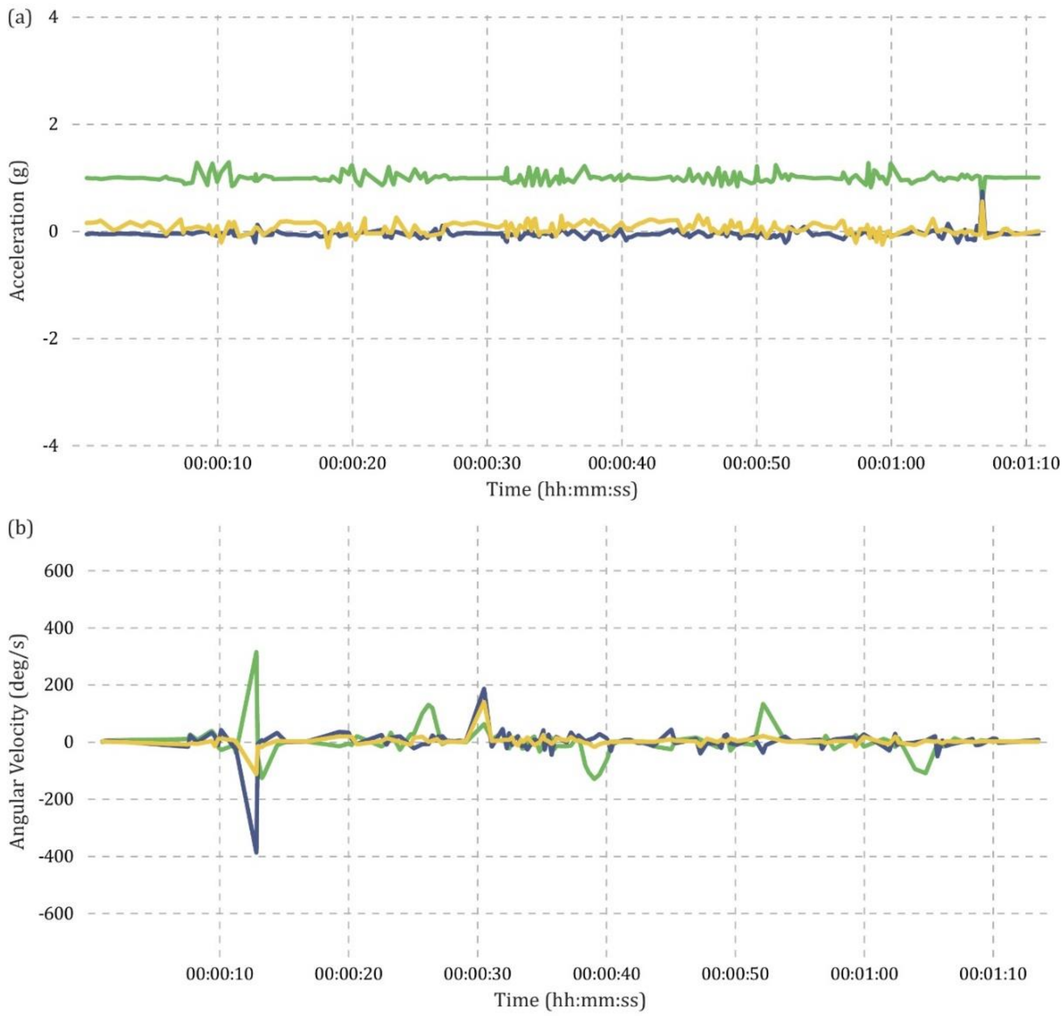

Figure 3.18 Data taken at the waist for the walking activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

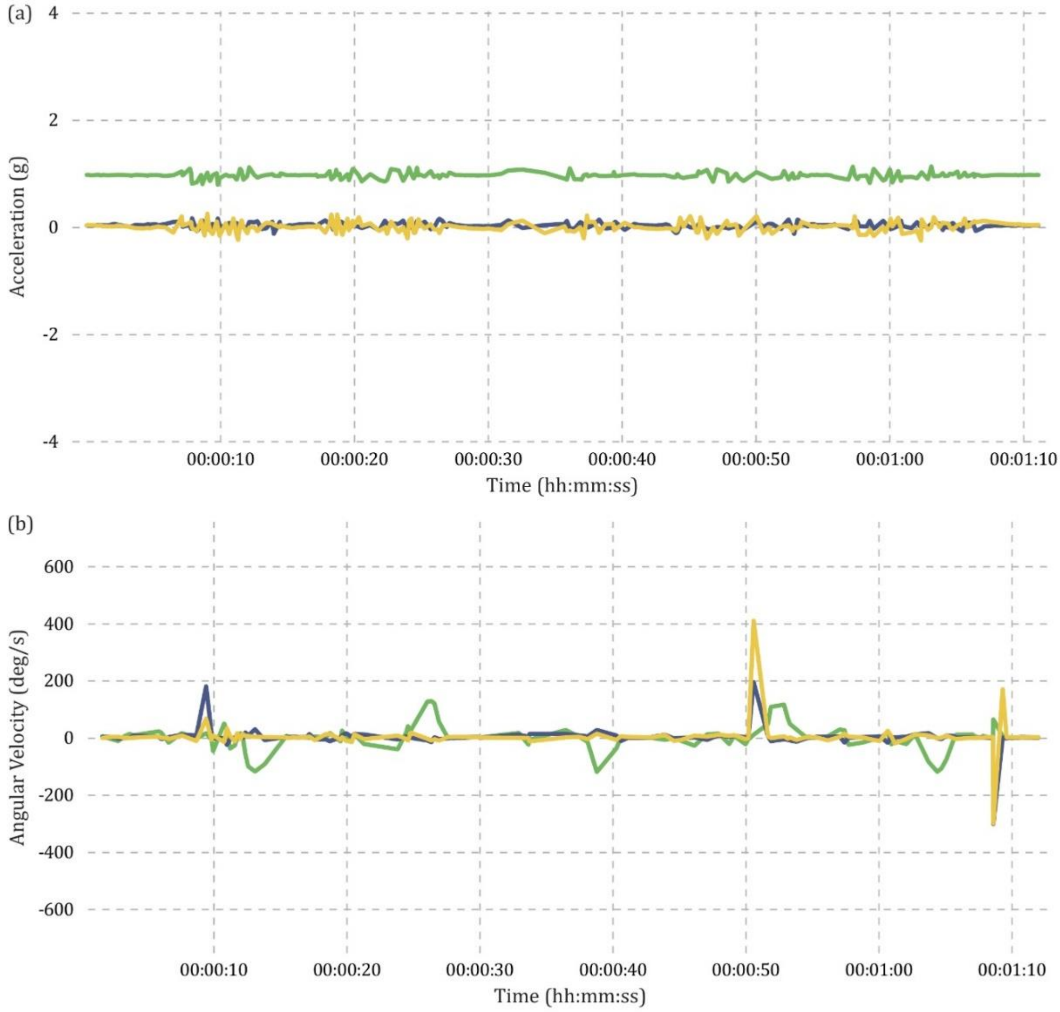

Figure 3.19 Data taken at the lower back for the walking activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

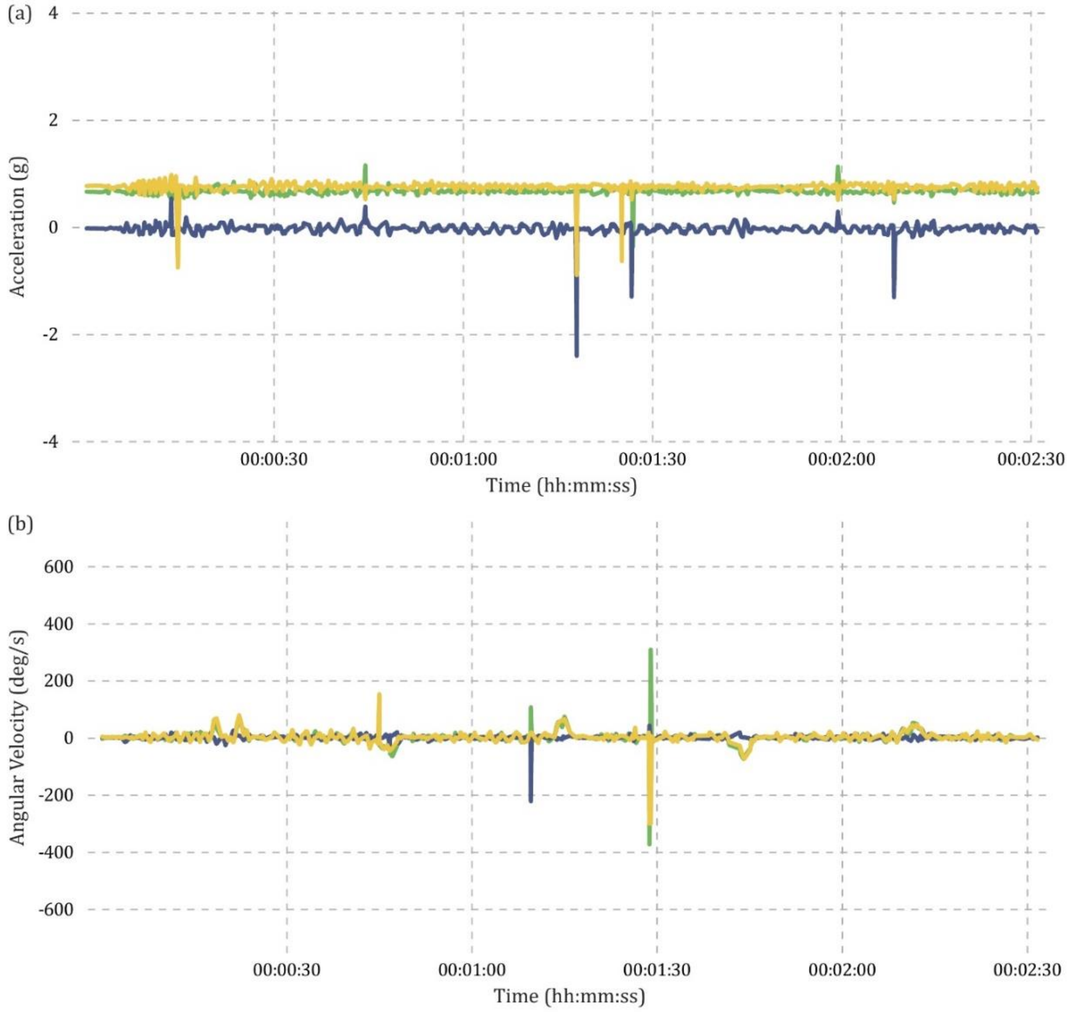

Figure 3.20 Data taken at the chest for the walking slowly activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

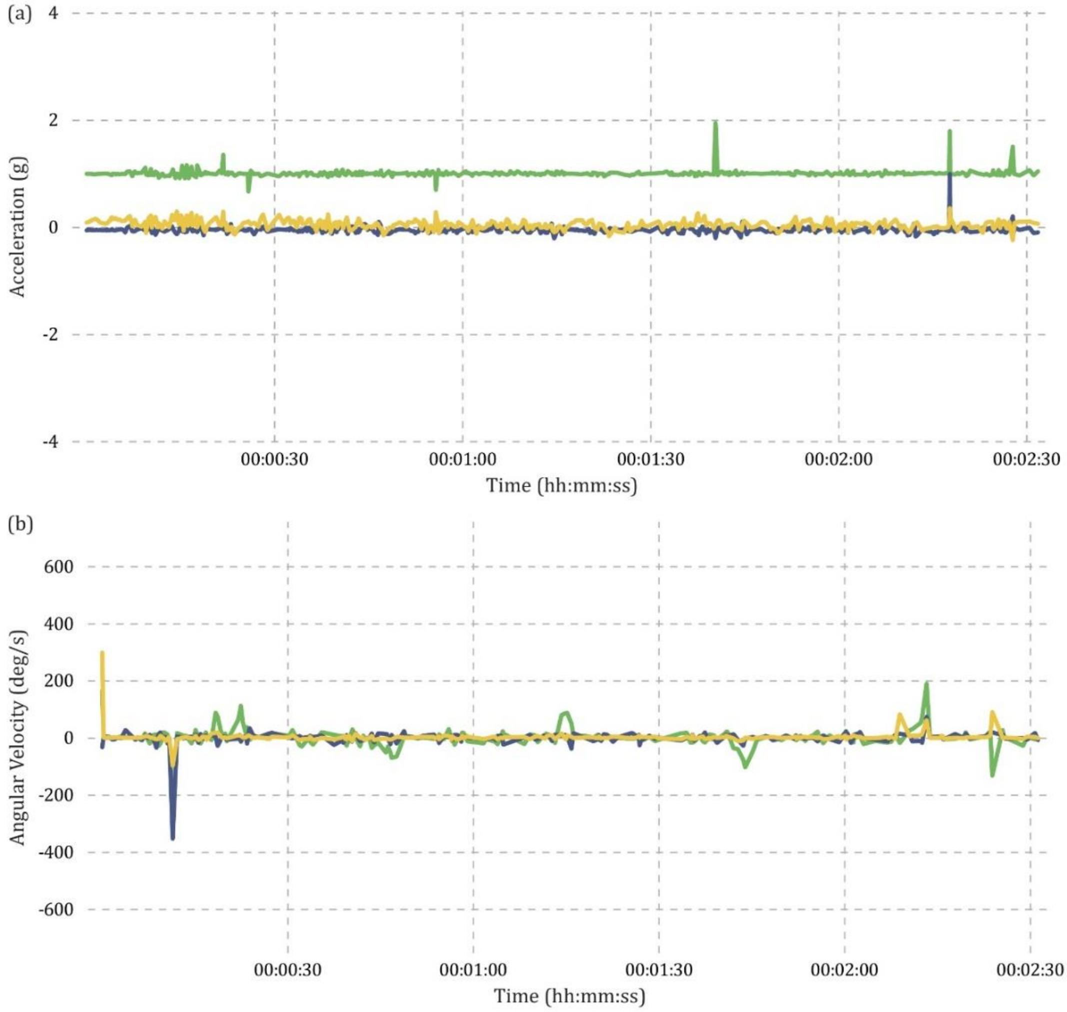

Figure 3.21 Data taken at the waist for the walking slowly activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

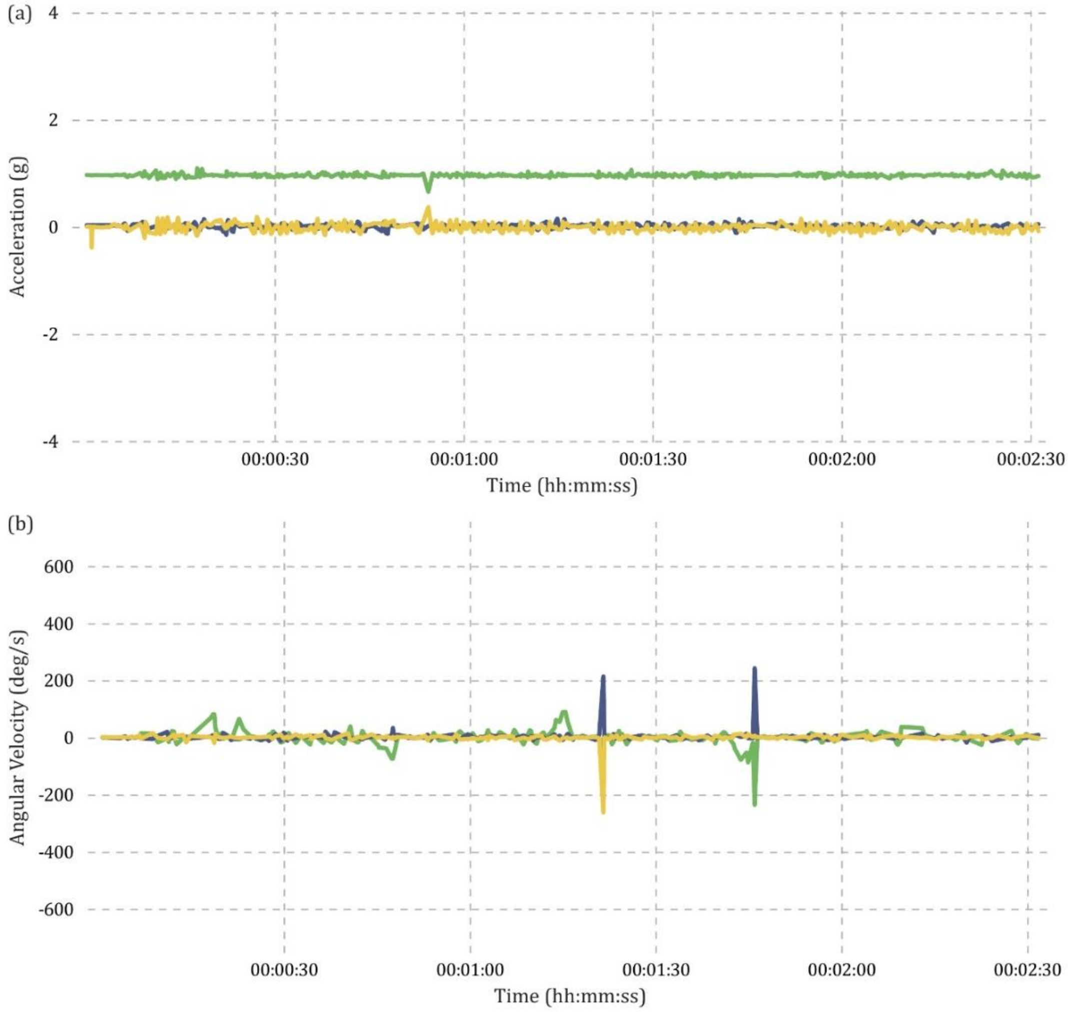

Figure 3.22 Data taken at the lower back for the walking slowly activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

All the locations where the accelerometer data was observed, appeared to be similar (see Figure 3.17 - Figure 3.22). There is some change in the acceleration as the participant is moving but it is not particularly significant, especially when compared to the thigh and ankle (shown later).

In the gyroscope data, the turn at the end of each repeat can be seen for both walking and walking slowly. For the chest tracker, there is a change in the x-axis and z-axis which is smaller than the change in the x-axis for the waist and lower back trackers (74deg/s for the chest compared to 114deg/s for the waist, for the first turn). This is because the turn motion is led by the lower body, therefore as the chest is higher up, the angular velocity is slower.

The walking activity showed much less change in the chest, waist, and lower back for both the accelerometer and gyroscope data compared to the thigh.

3.3.2.2 SITTING ADLS

Figure 3.23, Figure 3.25 and Figure 3.27 present the data at the chest, waist and lower back respectively for sitting on a chair.

Figure 3.24, Figure 3.26 and Figure 3.28 present data taken at the chest, waist, and lower back for sitting on a stool respectively.

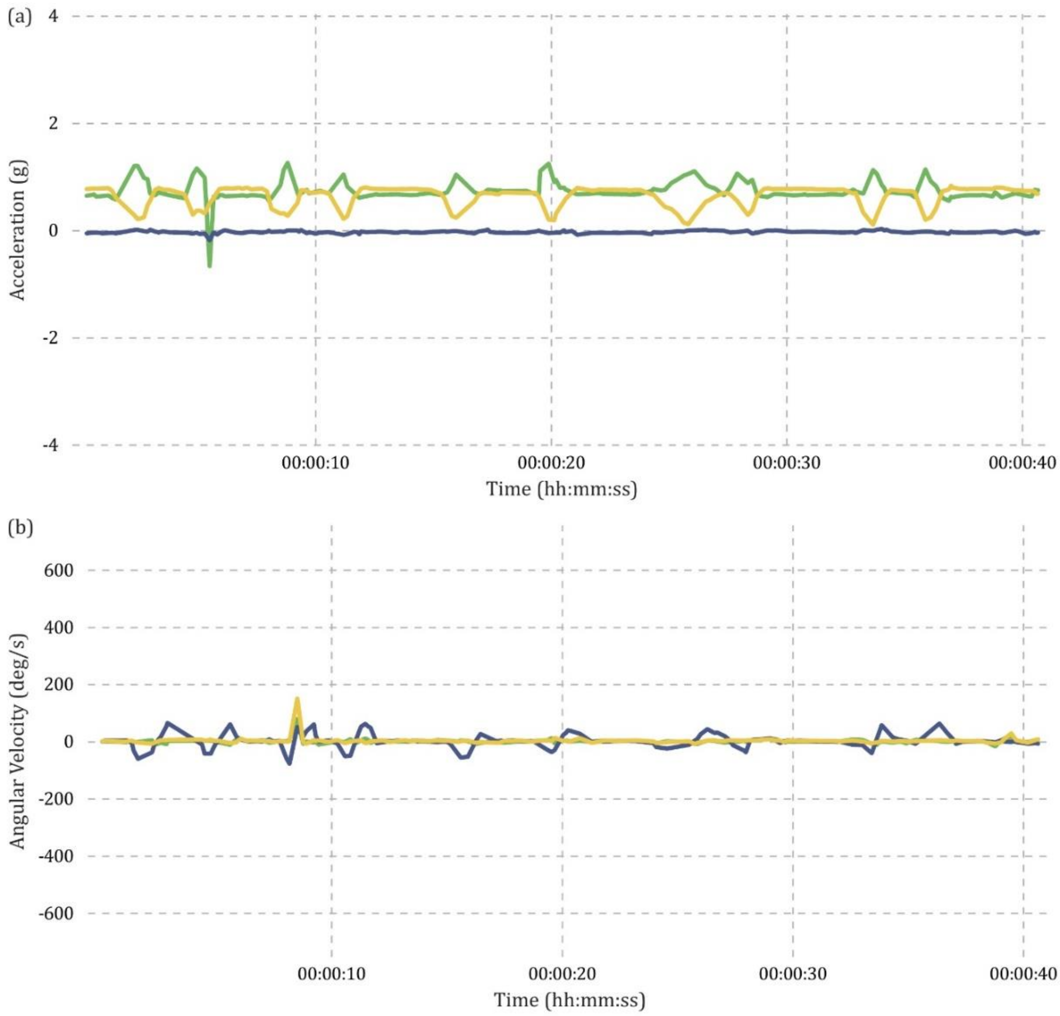

Figure 3.23 Data taken at the chest for sitting on a chair. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

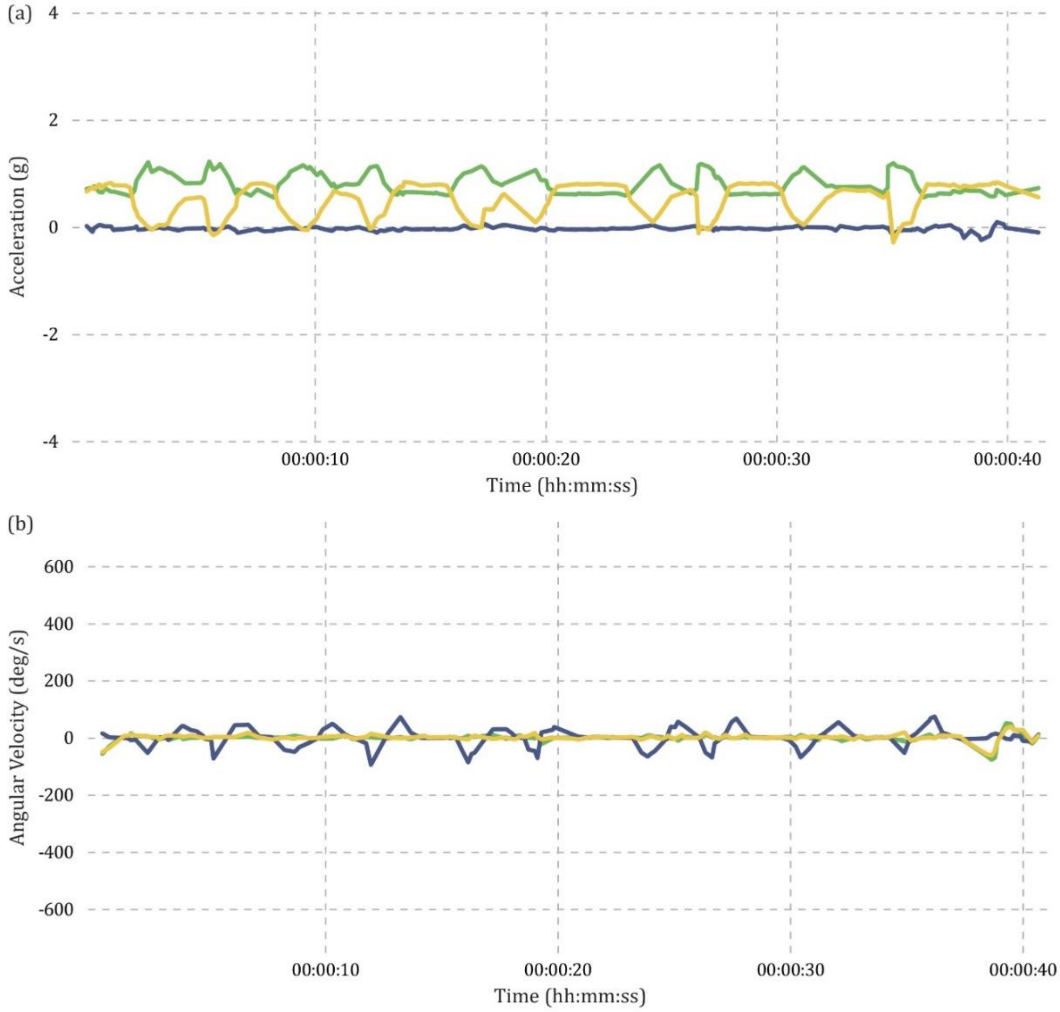

Figure 3.24 Data taken at the chest for sitting on a stool. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

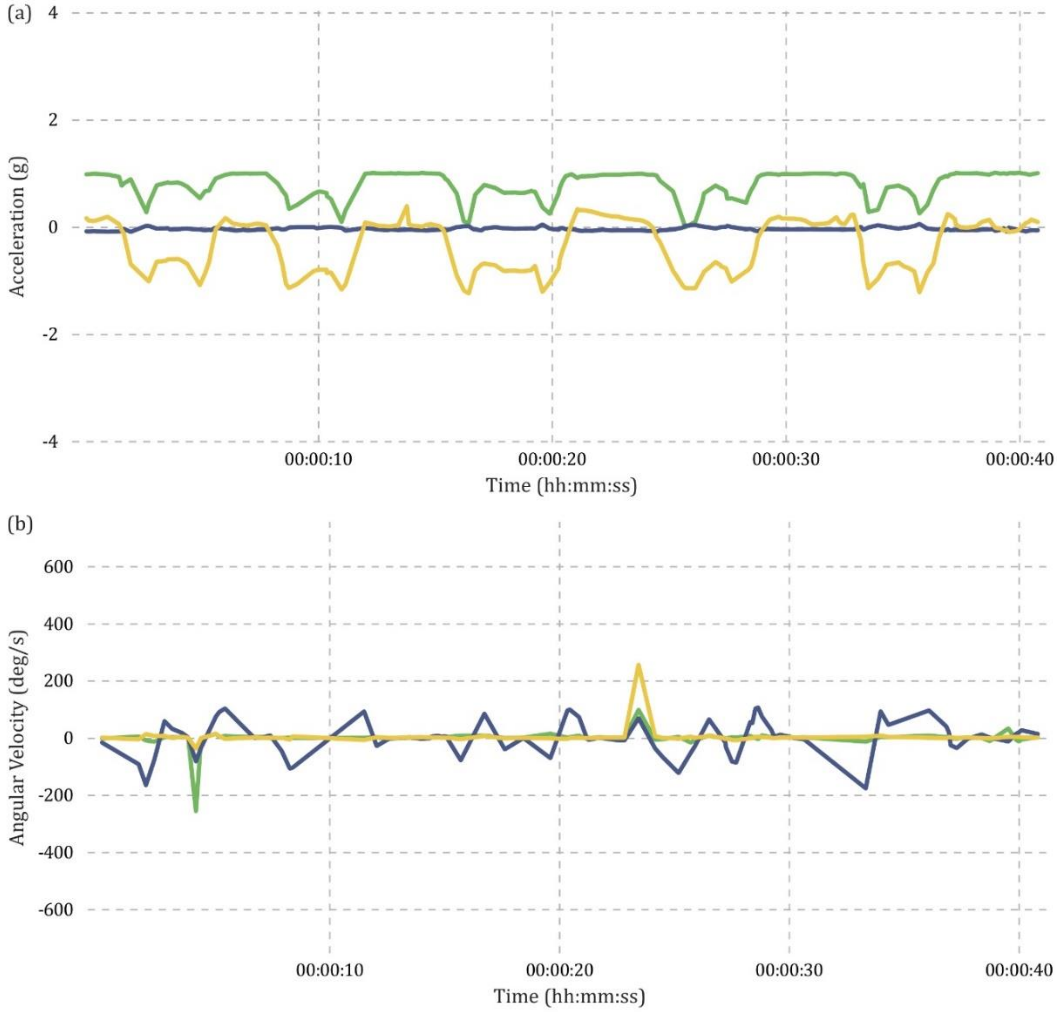

Figure 3.25 Data taken at the waist for sitting on a chair. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

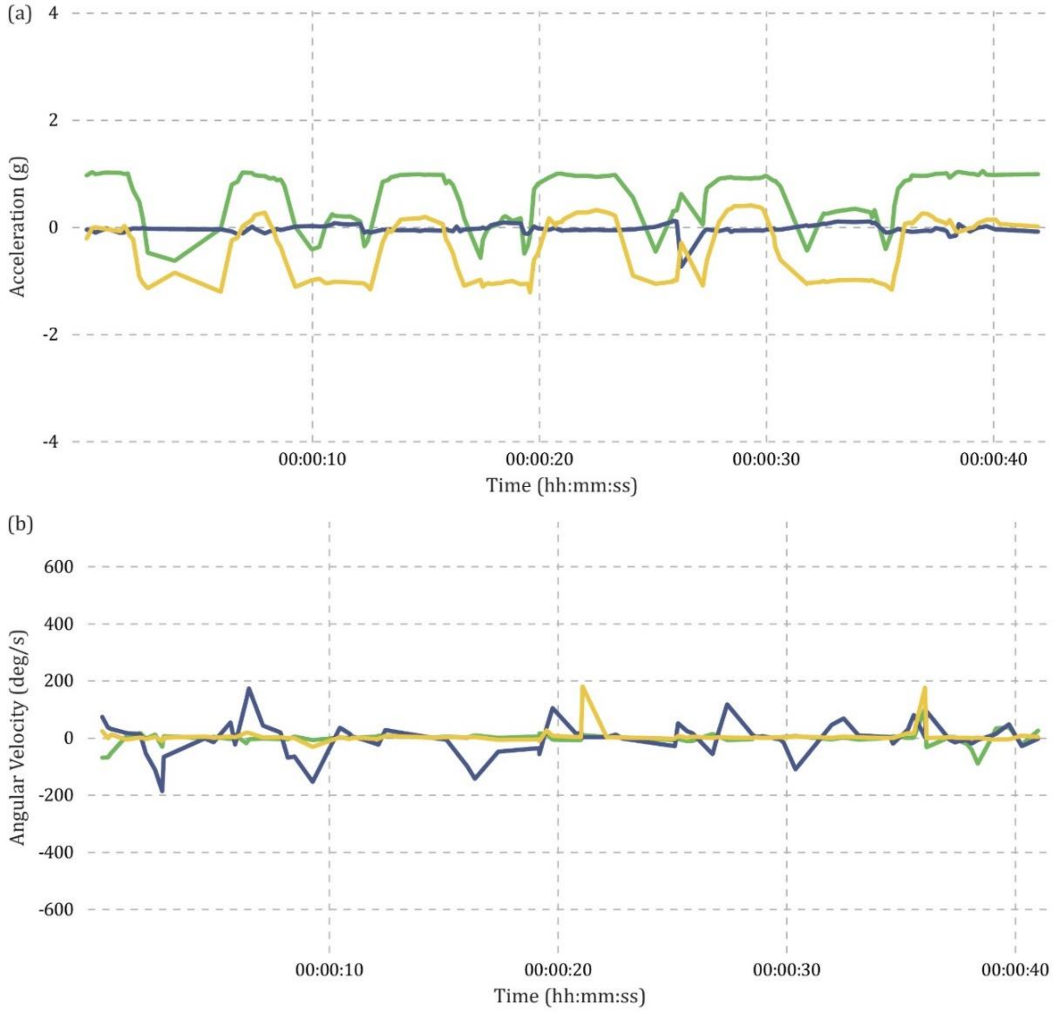

Figure 3.26 Data taken at the waist for sitting on a stool. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

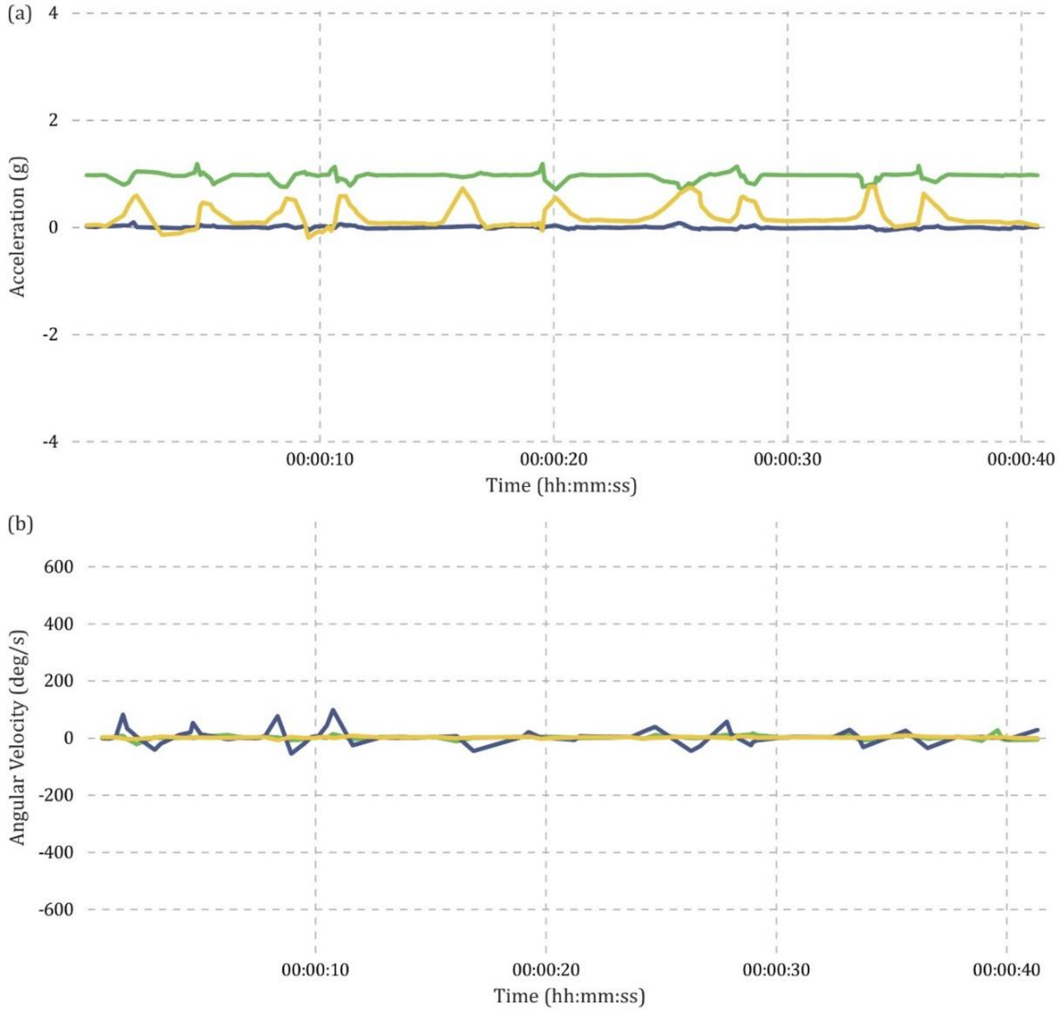

Figure 3.27 Data taken at the lower back for sitting on a chair. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

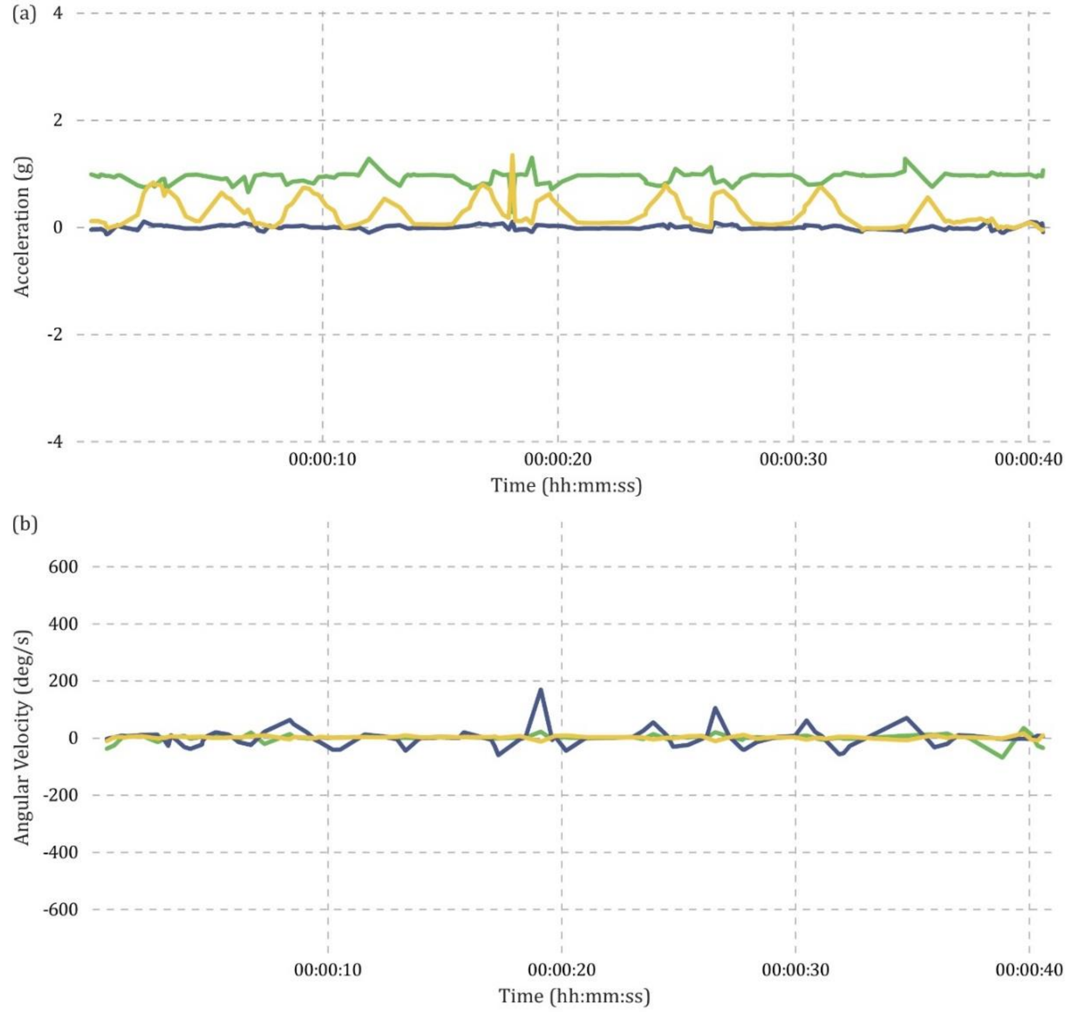

Figure 3.28 Data taken at the lower back for sitting on a stool. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The acceleration data seen for the chest, waist, and lower back for both sitting on a chair and sitting on a stool, show similar patterns. Figure 3.23a and Figure 3.24a, show the chest data for sitting on a chair and sitting on a stool at the chest respectively. The pattern seen in both figures shows as the participant is sitting there is an increase and then a decrease in the x-axis and as the participant returns to a standing position, there is also an increase, followed by a decrease in the x-axis. Whilst the participant is sitting still and standing still there is no change in the x-axis acceleration. The z-axis has the same pattern but in the reverse direction. The y-axis does not show significant change during any of the movements.

The difference observed for the waist and lower back compared to the chest, is due to the orientation of the sensor, which alters the direction of change in the x-axis and the z-axis. At the waist, the x-axis follows the same direction as the z-axis. At the lower back, compared to the chest, the acceleration in the x-axis and z-axis both change in the opposite direction. For the waist and the lower back, the x-axis has a smaller change than the z-axis for both sitting on a chair and sitting on a stool. At the chest, there is a smaller change in the x-axis compared to the z-axis but only for sitting on a stool. This is possibly because the chest is higher up on the body compared to the waist and lower back, which results in a larger acceleration change in the x-axis as the participant sits and stands.

Additionally, the lower back has smaller changes in acceleration on the x-axis compared to the chest and waist, for both sitting on a chair and sitting on a stool. The waist has the largest change in acceleration in the z-axis for both sitting on a chair and sitting on a stool. The change in acceleration in all three axes for the chest, waist and lower back for both sitting on a chair and sitting on a table can be seen in Table 3.1 and Table 3.2 respectively.

Table 3.1 Absolute change in acceleration in the three axes for sitting on a chair at the chest, waist and lower back.

Location	x-axis	y-axis	z-axis
Chest	0.479	0.036	0.581
Waist	0.789	0.067	1.239
Lower Back	0.100	0.013	0.581

Table 3.2 Absolute change in acceleration in the three axes for sitting on a stool at the chest, waist and lower back.

Location	x-axis	y-axis	z-axis
Chest	0.581	0.022	0.734
Waist	1.355	0.057	1.227
Lower Back	0.142	0.051	0.666

The gyroscope data at the chest in Figure 3.23b (sitting on a chair) and Figure 3.24b (sitting on a stool) shows changes in angular velocity along the y-axis. There is a decrease and increase in the y-axis as the participants sit and the same pattern as they stand. This is like the pattern observed at the thigh when kneeling (Figure 3.11b). The gyroscope data for the waist, like the chest, is only on the y-axis and follows a similar pattern. The gyroscope data at the lower back data also follows the same pattern as the chest and waist, but it is reversed i.e., increase then decrease in the y-axis.

Figure 3.29, Figure 3.30 and Figure 3.31 display the data taken at the chest, waist and lower back respectively for the kneeling activity.

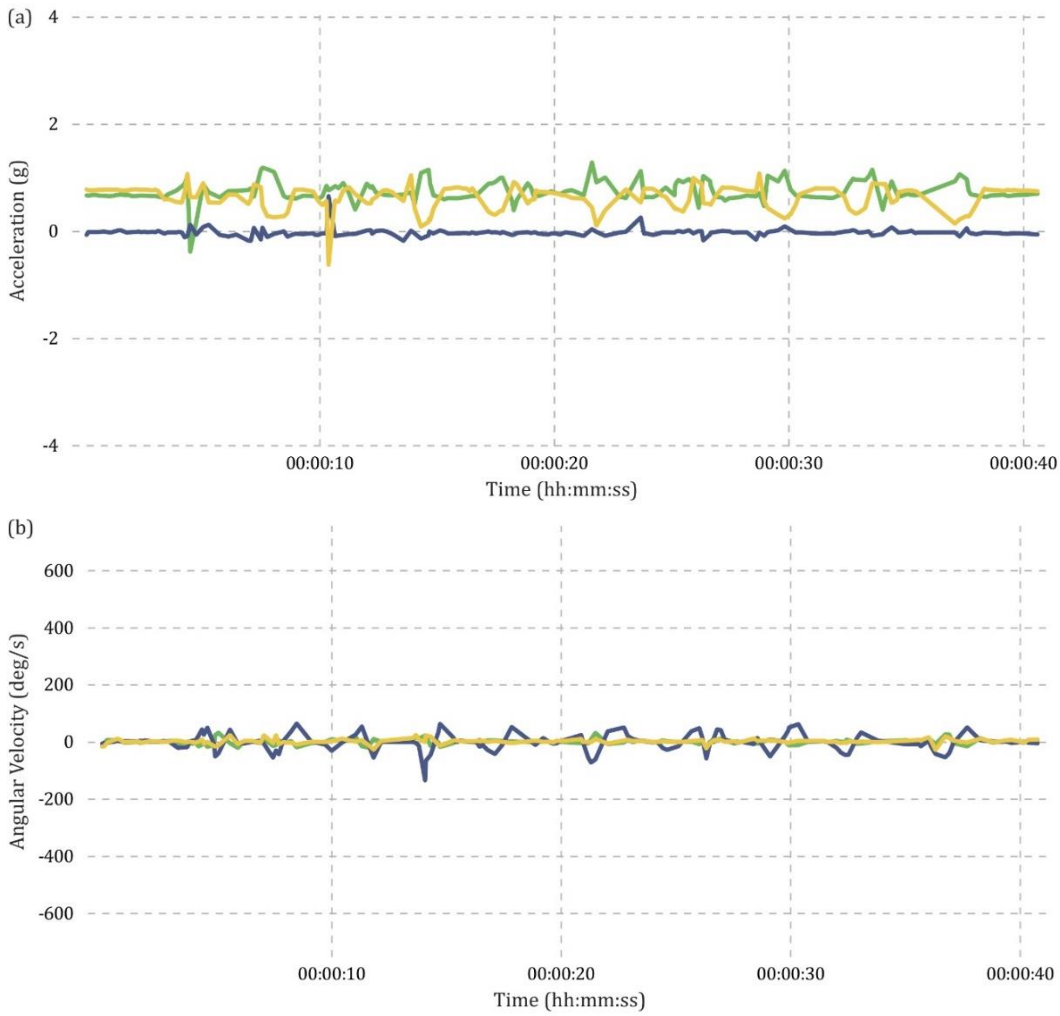

Figure 3.29 Data taken at the chest for the kneeling activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The acceleration data from the chest during the kneeling activity is unclear due to the amount of movement in the chest as the participant bends to get to their knees. The acceleration data does appear to follow the same pattern as the sitting on a chair and sitting on a stool activities. The gyroscope data, although not as clear as in Figure 3.23b and Figure 3.24b, also follows the same pattern.

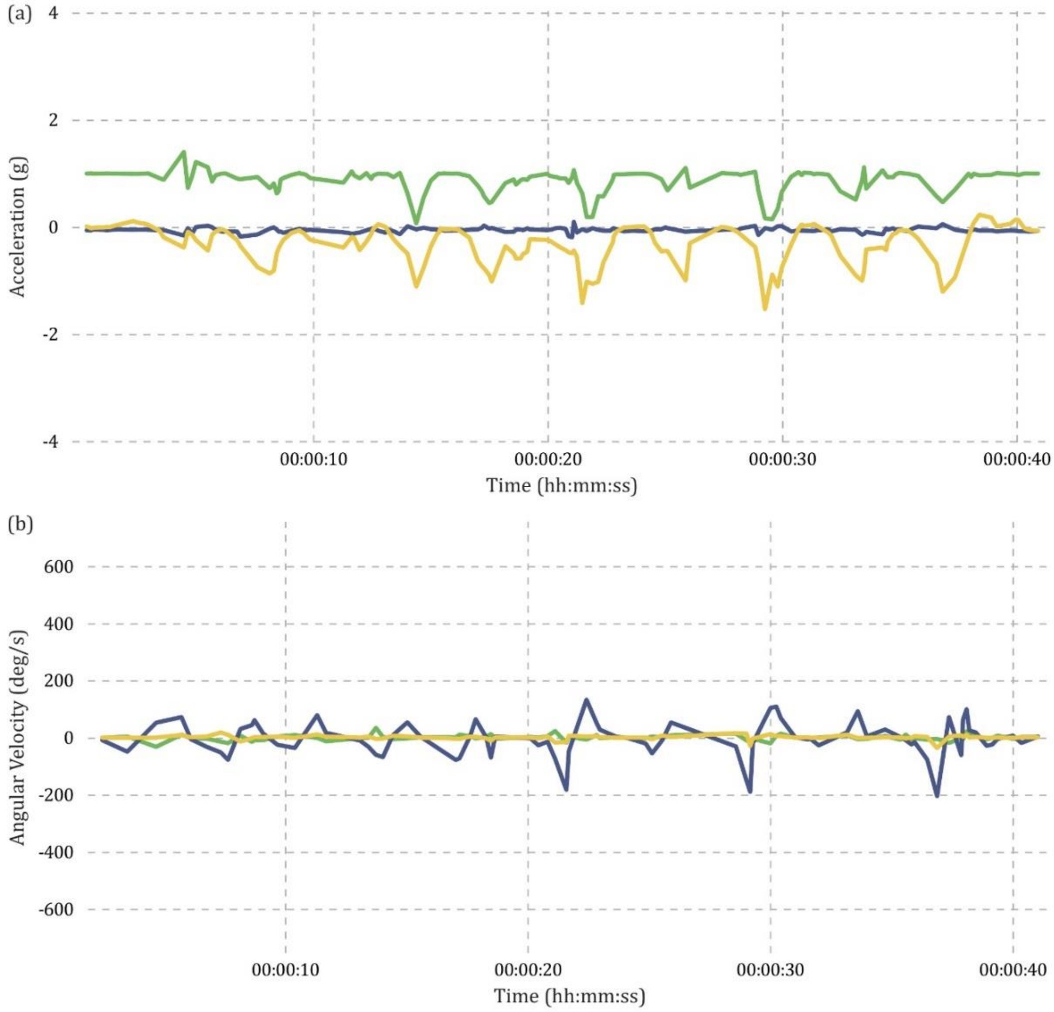

Figure 3.30 Data taken at the waist for the kneeling activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.30a shows the acceleration data for kneeling, which follows a similar pattern to sitting on a chair and sitting on a stool. Both the z-axis and x-axis decrease and increase as the participant kneels. As the participant stands back up, the z-axis and x-axis decrease then increase, this decrease in acceleration is larger than when the participant is sitting. The gyroscope data in Figure 3.30b follows the same pattern as seen in Figure 3.25b and Figure 3.26b, with a decrease and increase when the participant is kneeling and the same for returning to the standing position. These patterns are clearer than for the chest as there is more movement made in at chest as the participant is kneeling compared to the waist.

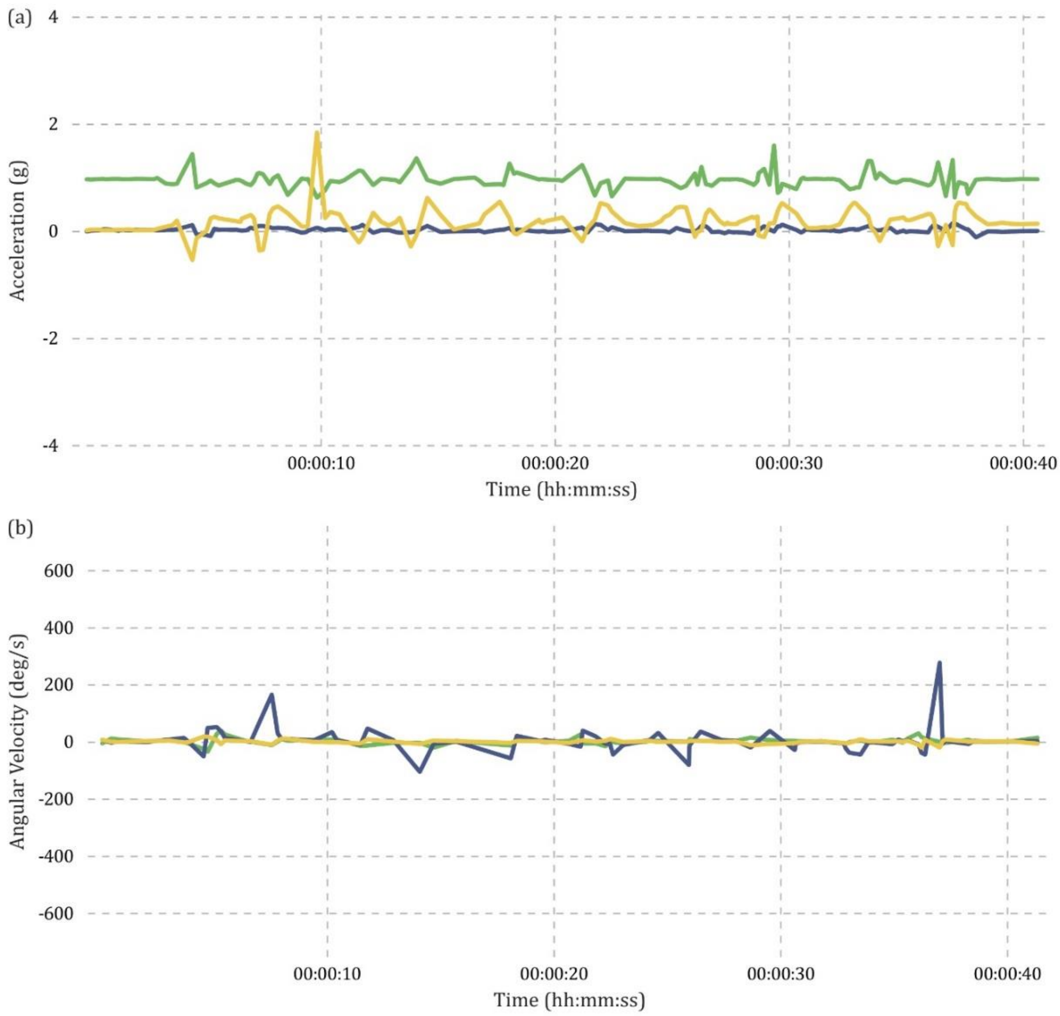

Figure 3.31 Data taken at the lower back for the kneeling activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

As observed for the chest, the acceleration data for the lower back in Figure 3.31a does not present a clear pattern. With the help of the gyroscope data in Figure 3.31b and the video, it became easier to find where the pattern is in the acceleration data. The gyroscope data follows the same patterns described in Figure 3.27b and Figure 3.28b.

3.3.2.3 OTHER ADLS

The figures in this section present the data from reaching high to low, 'Turn 180' and the 'Timed Up and Go' test.

Figure 3.32, Figure 3.33 and Figure 3.34 show the data for reaching high to low at the chest, waist and lower back respectively.

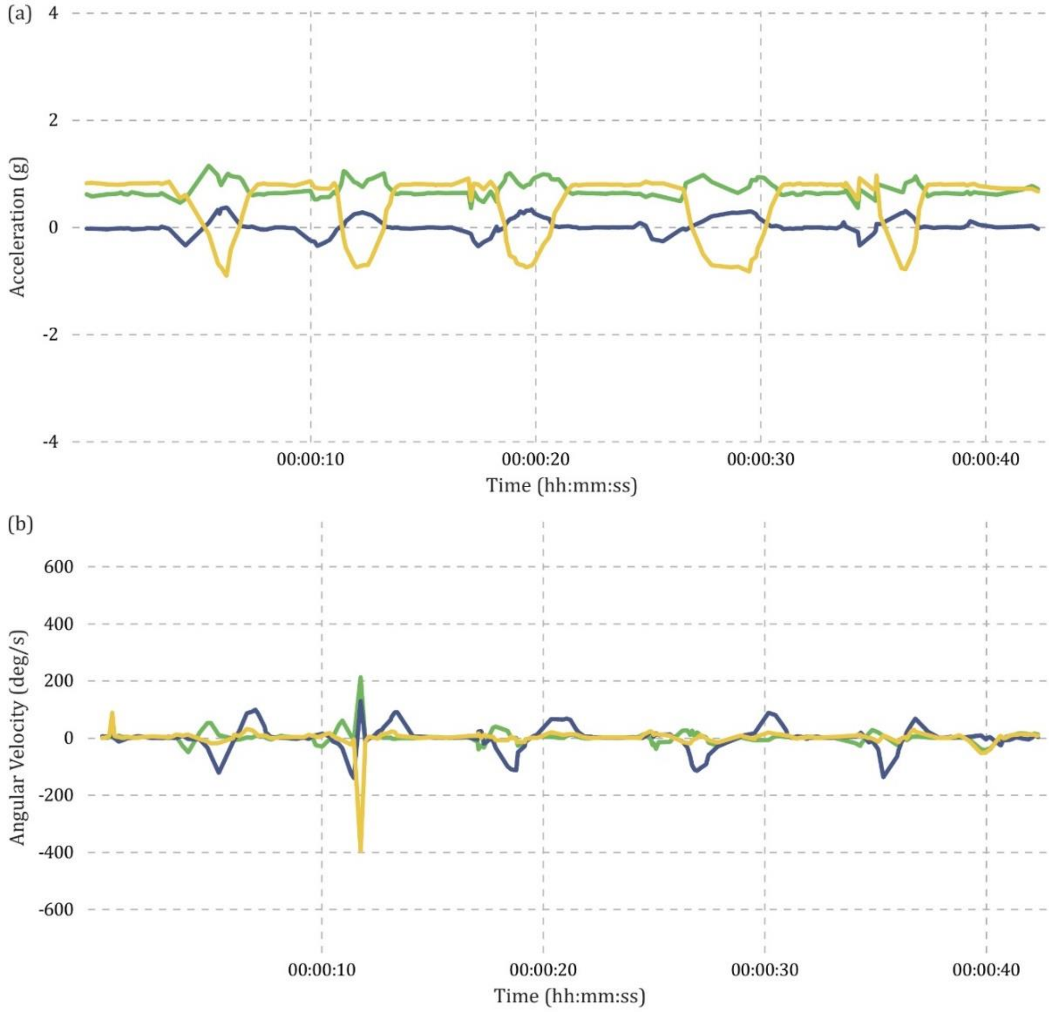

Figure 3.32 Data taken at the chest for reaching high to low. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The acceleration data from Figure 3.32a shows a large decrease in the z-axis (1.73; first repeat) and an increase in the y-axis and x-axis (-0.02 – 0.34 and 0.6 – 1.14 respectively; first repeat) at the point of bending. However, just before this, there is a decrease in both the y-axis and x-axis. This was when the participant was reaching high which was done by reaching up with the hand and moving on to the toes (confirmed by the video). Therefore, there is some movement of the centre of the body, just not as much as when bending down. In the gyroscope data, there is a decrease and increase in the angular velocity in the x-axis at the point of reaching up and a larger decrease and increase in the y-axis at the point of bending down.

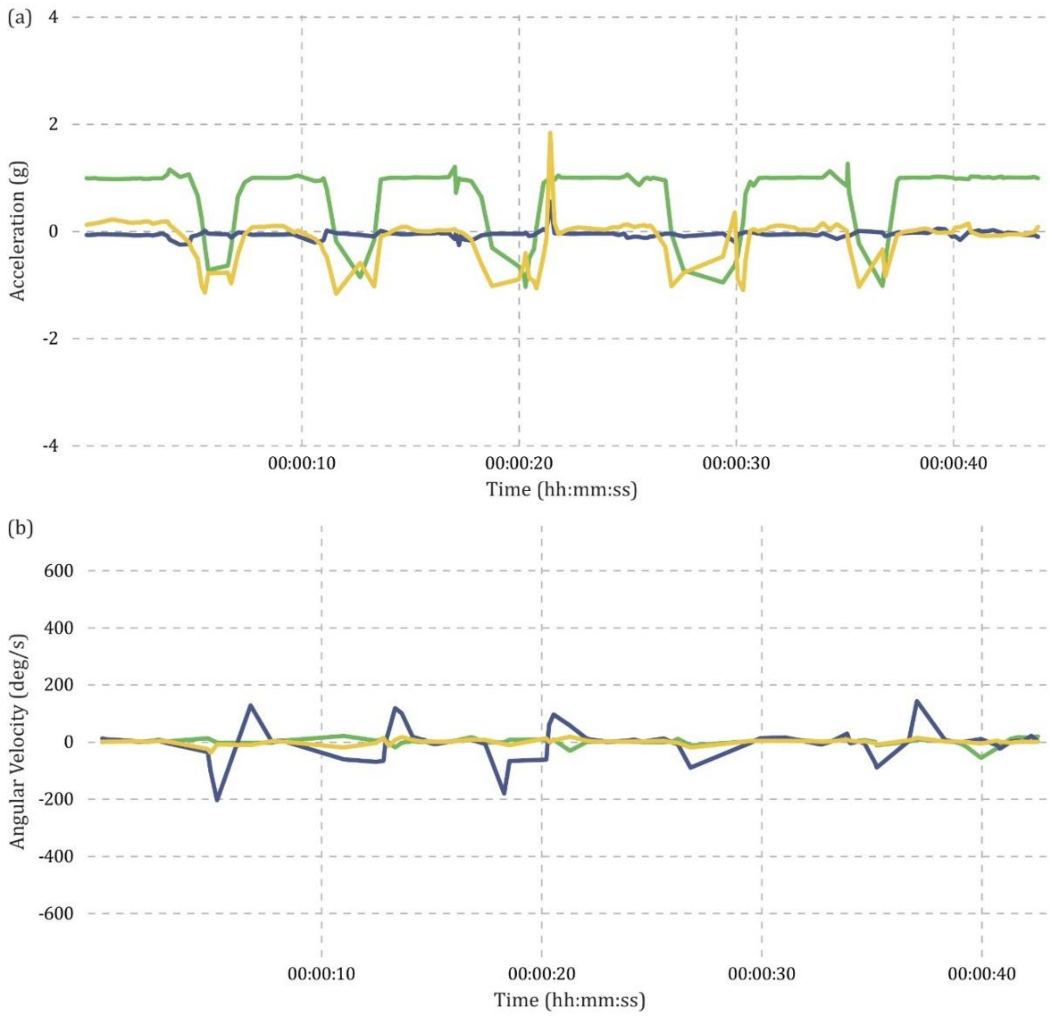

Figure 3.33 Data taken at the waist for reaching high to low. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Unlike at the chest, the acceleration changes at the waist only changed in the x-axis and the z-axis, which both decrease for the reaching low portion of the activity. There is some movement in the y-axis as the activity was being performed, however, this was not significant. The change in acceleration for both the x-axis and z-axis was larger compared to the chest and the lower back. Likewise, as seen in Figure 3.33b, the angular velocity change in the y-axis was the largest at the waist. The angular velocity in the x-axis and z-axis did not change significantly.

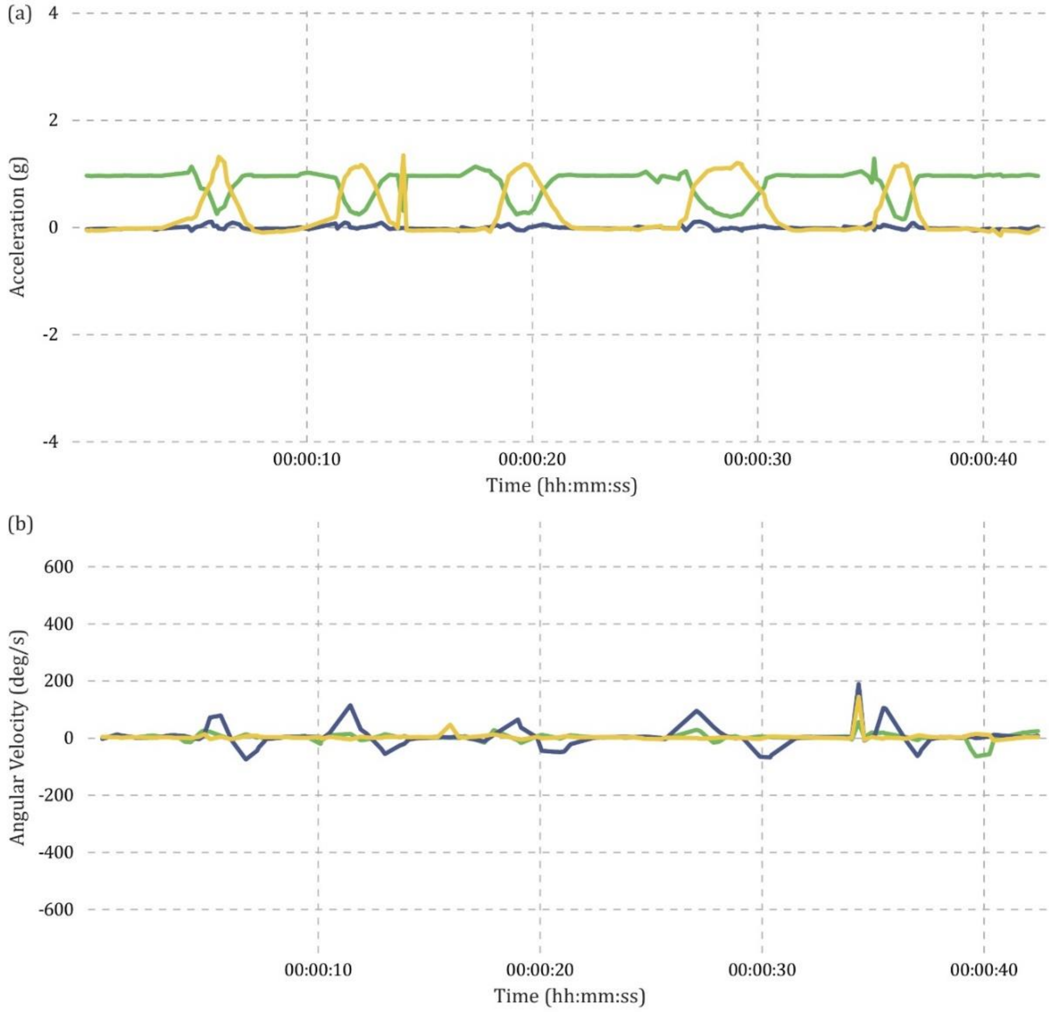

Figure 3.34 Data taken at the lower back for reaching high to low. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The acceleration data shown in Figure 3.34a taken at the lower back showed an increase in the z-axis and a decrease in the x-axis during the activity. The change in acceleration is similar to the change in acceleration in Figure 3.32a. The y-axis acceleration did not show any significant changes like at the waist. The gyroscope data showed the same pattern as seen in Figure 3.33b, but it was inverted due to the orientation of the tracker.

Figure 3.35, Figure 3.36 and Figure 3.37 show the data for turning at the chest, waist and lower back respectively.

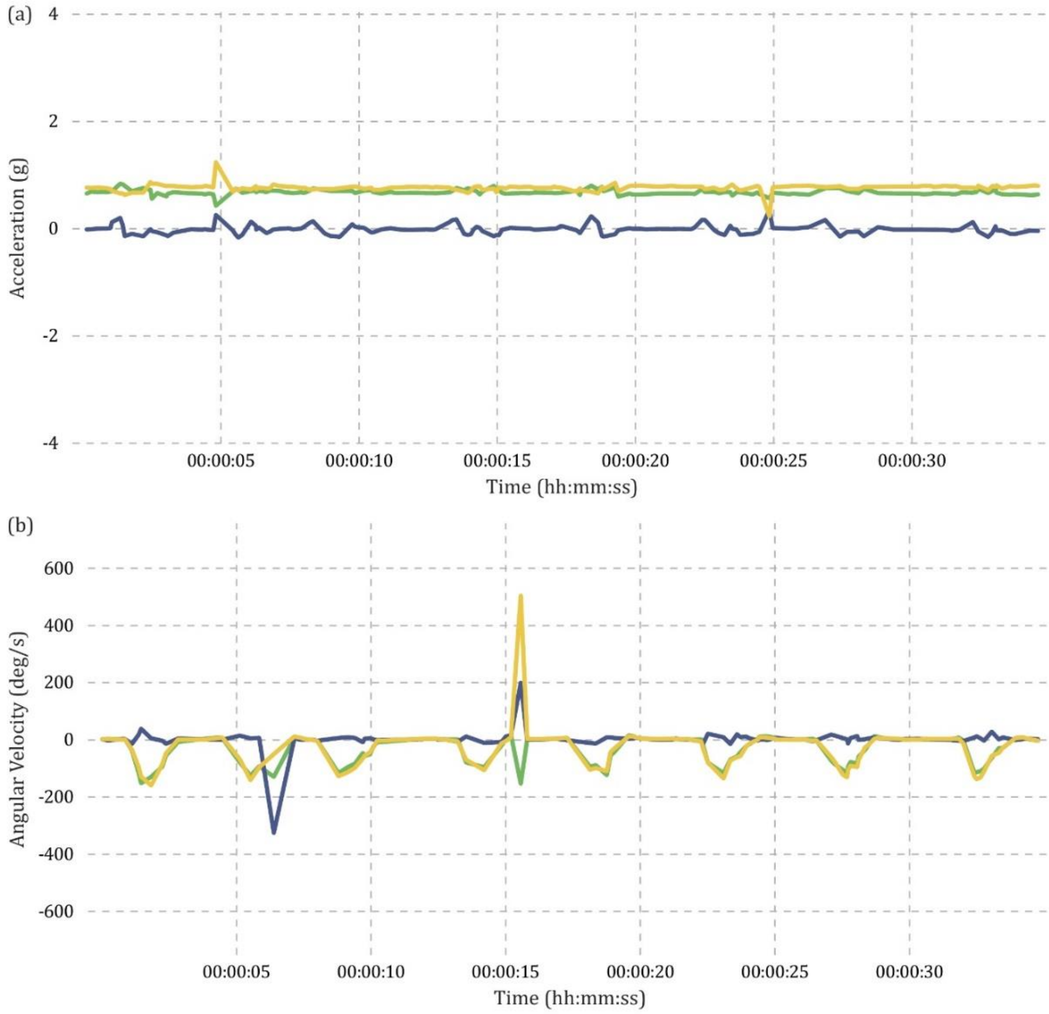

Figure 3.35 Data taken at the chest for the turning activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

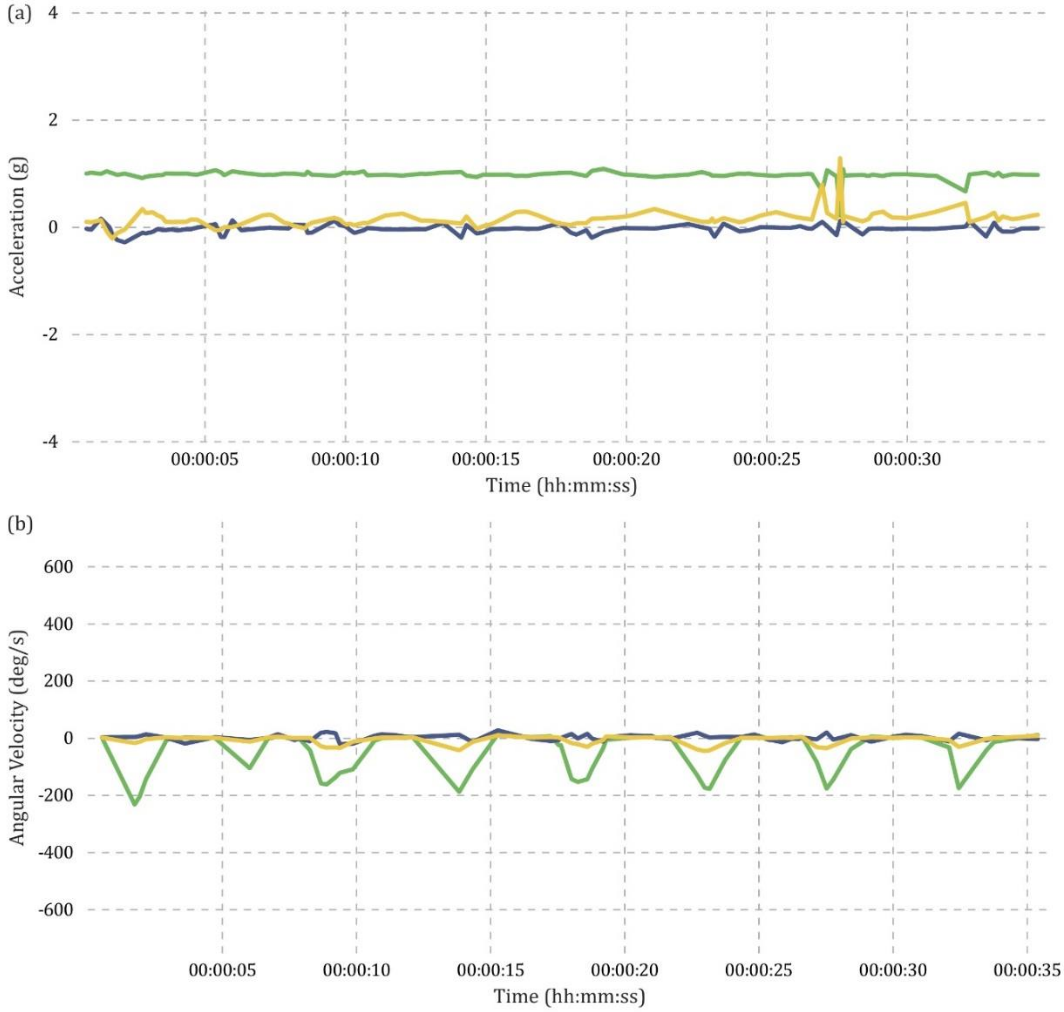

Figure 3.36 Data taken at the waist for the turning activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

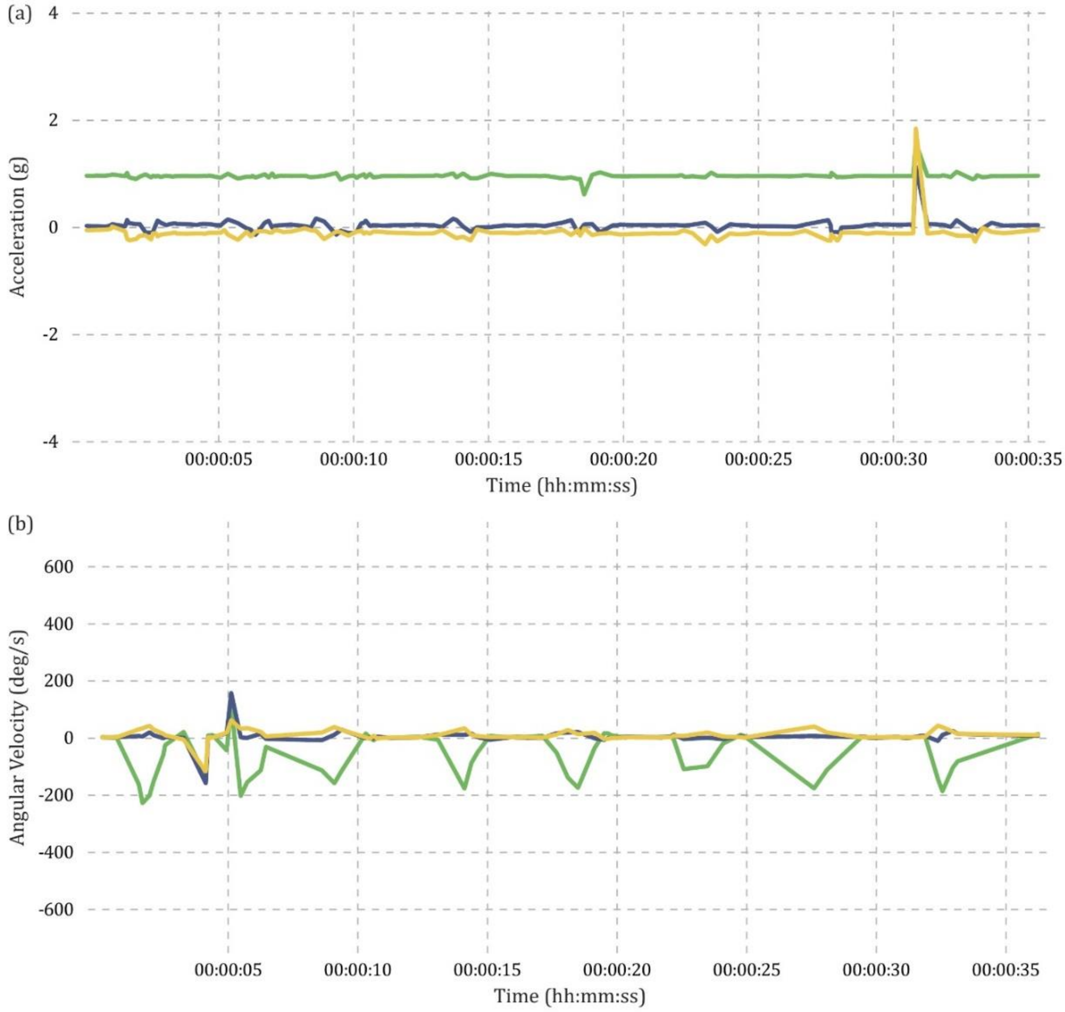

Figure 3.37 Data taken at the lower back for the turning activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.35a, Figure 3.36a and Figure 3.37a all showed some change in acceleration at the point of each turn; however, the magnitude of this change was minimal. The gyroscope data in Figure 3.35b clearly shows the eight turns, and for each turn, there was a decrease in the x-axis and z-axis. Figure 3.36b and Figure 3.37b also clearly showed the eight turns, however here for each turn there was a decrease in the x-axis only. There were some fluctuations in the angular velocity on the y-axis and z-axis, but they appear to be from general movement rather than part of the pattern of the turn.

Figure 3.38, Figure 3.39 and Figure 3.40 shows the data for the 'Timed Up and Go' test at the chest, waist and lower back respectively.

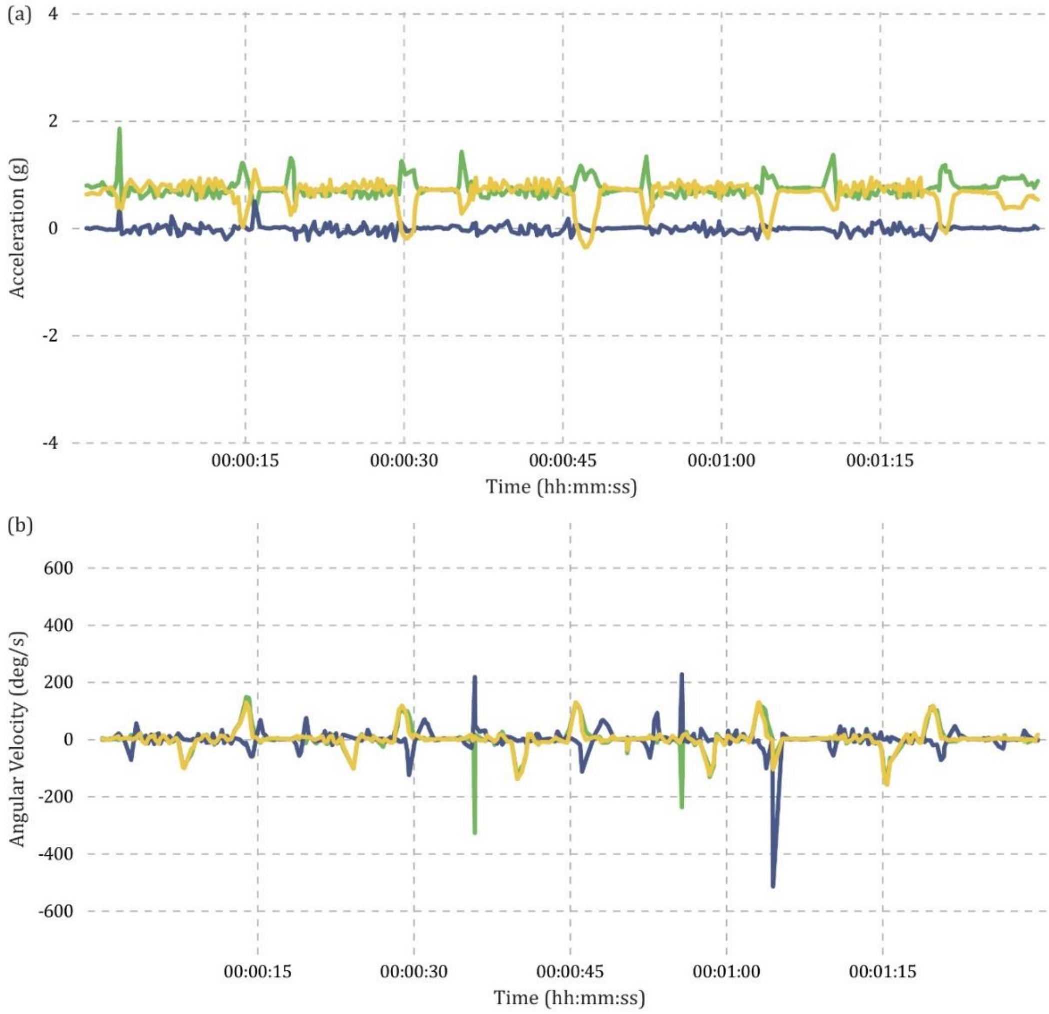

Figure 3.38 Data taken at the chest for the 'Timed Up and Go' test. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The acceleration in Figure 3.38a looked like a combination of the 'sitting ADLs' seen in Figure 3.23a and Figure 3.24a. Fluctuations in all three axes could be observed whilst the participant was walking, and changes in the z-axis and x-axis associated with the participant sitting back down could be seen, as previously observed in Figure 3.23b. The point where the participant stood up at the being of the activity cannot be clearly identified. This can be in the gyroscope data as there is a decrease and increase in the y-axis at the point of standing up. When the participant turns, there is a change in the z-axis and x-axis as seen in Figure 3.35b. Additionally, the gyroscope data has a decrease and increase in the y-axis as the participant sits back down, which is the same as when they stand just like in Figure 3.23b.

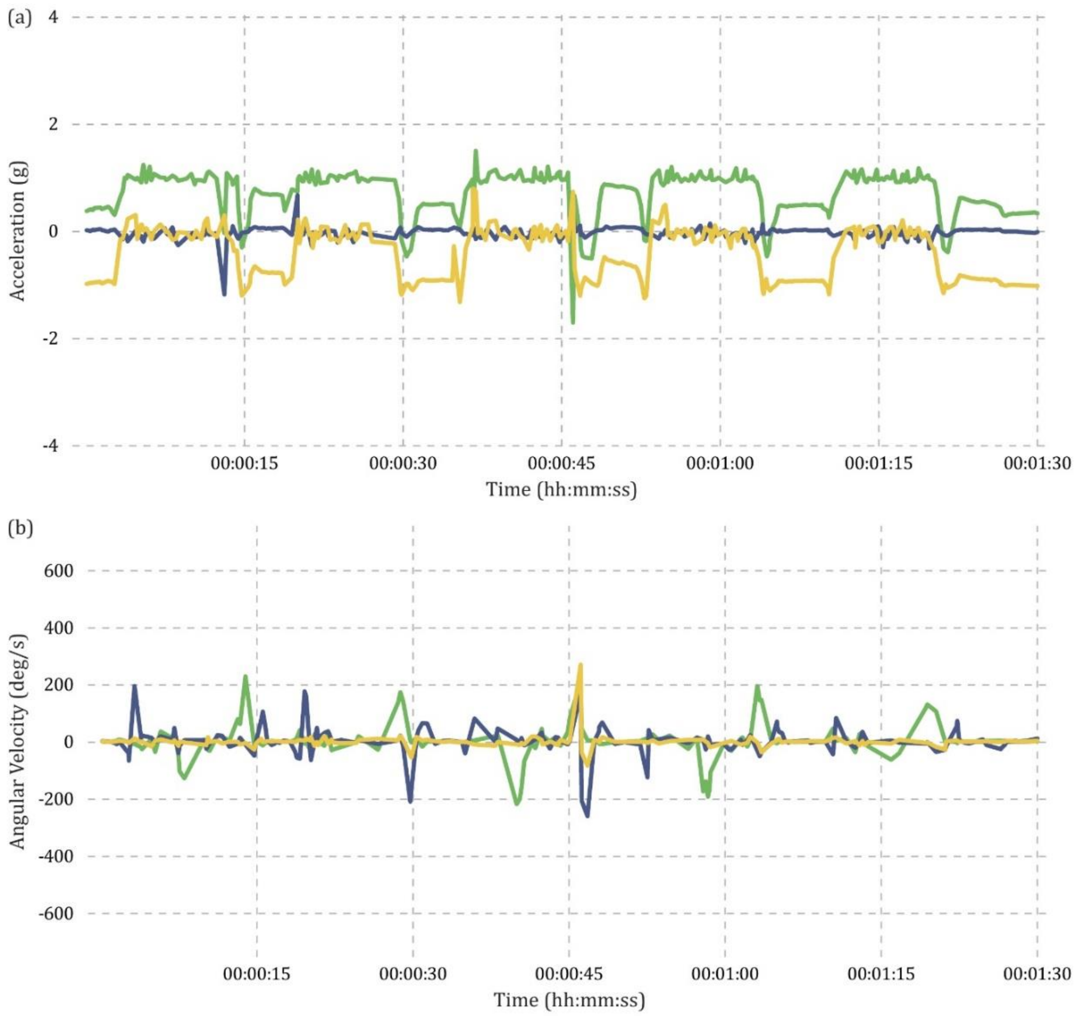

Figure 3.39 Data taken at the waist for the 'Timed Up and Go' test. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

In Figure 3.39a an increase in the acceleration in the x-axis and z-axis as the participant stood could be observed, there are some fluctuations in the all three axes during walking, and there is a decrease in the x-axis and z-axis as the participant sits back down. The stand and sit sections of the activity can be seen in the gyroscope data as a decrease and increase in the y-axis (respectively), similar to the pattern seen in Figure 3.25b. The gyroscope data also showed the two turns per activity, which correspond to a change in the angular velocity on the x-axis.

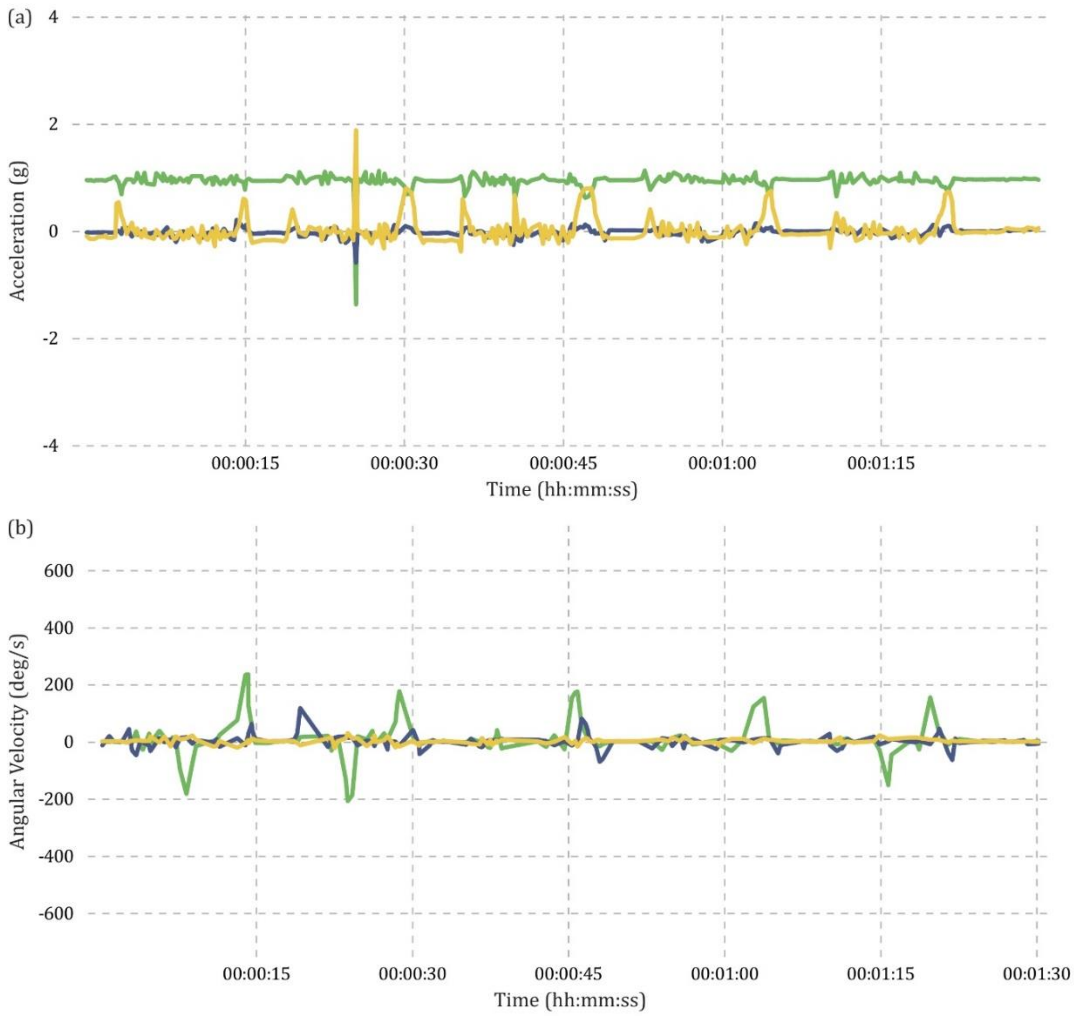

Figure 3.40 Data taken at the lower back for the 'Timed Up and Go' test. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The acceleration data in Figure 3.40a is similar to Figure 3.39a, as the acceleration data clearly shows when the participant stands and sits (unlike in Figure 3.38a). This can be seen in Figure 3.40a as an increase in the acceleration on the z-axis and a decrease in the x-axis. The changes in the x-axis and z-axis acceleration are much smaller for the lower back than the chest and the waist, as seen in the sitting on a chair. This is likely because the lower back moves the least whilst a person is sitting, resulting in a smaller change in acceleration. The chest has the longest distance to travel, and the waist incorporated the movement of the pelvis. The gyroscope data show a pattern similar to a combination of the patterns observed in Figure 3.27b and Figure 3.37b, which are for sitting on a chair and the turn activities respectively. There was an increase and decrease in the angular velocity in the y-axis when the participant stands and again as they sit. There is a change in the x-axis angular velocity as the participant turns during the activity.

3.3.2.4 Lying Down and Falling

Figure 3.41, Figure 3.42 and Figure 3.43 present the data taken at the chest, waist and lower back respectively, for lying down.

Figure 3.44, Figure 3.45 and Figure 3.46 present the fall data taken at the chest, waist and lower back respectively.

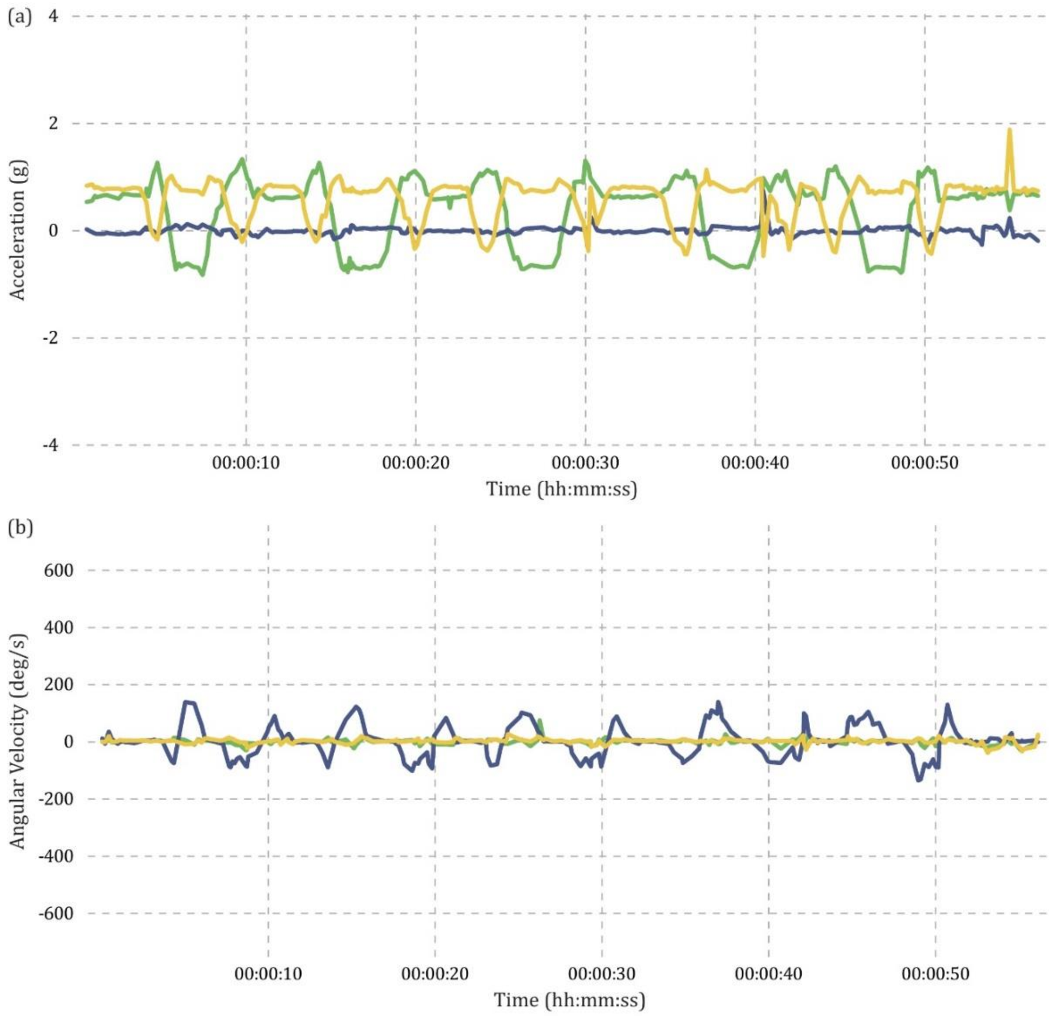

Figure 3.41 Data taken at the chest for lying down. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The accelerometer data in Figure 3.41a contains the pattern seen in Figure 3.23a (sitting on a chair taken at the chest), however, it has a decrease in the x-axis and increase in the z-axis as the participant is lying down, the z-axis returns to the level when the participant is standing, and the x-axis decreases to a much lower level. Figure 3.41b shows the gyroscope data with a similar pattern to that seen in Figure 3.23b.

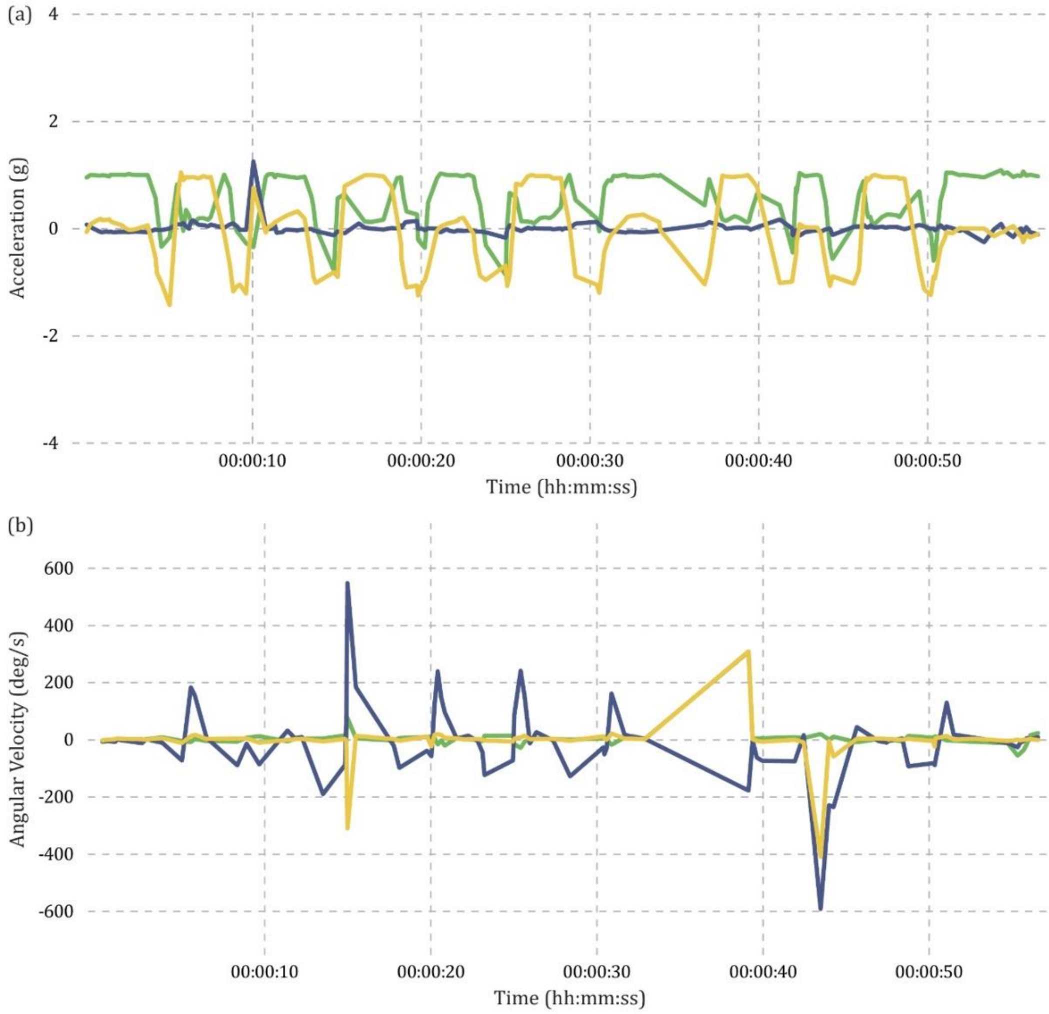

Figure 3.42 Data taken at the waist for lying down. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The accelerometer data in Figure 3.42a follows a similar pattern as seen in Figure 3.25a, but there is a more obvious increase in the z-axis as the participant is lying down compared to when they are sitting. This increase means that the z-axis level and the x-axis level are interchanged like they are in most of the thigh activities because of the distance travelled in the z-axis compared to the x-axis. Figure 3.42b shows the gyroscope data for the lying down activity which is the same pattern as the gyroscope data sitting on a chair in Figure 3.25b.

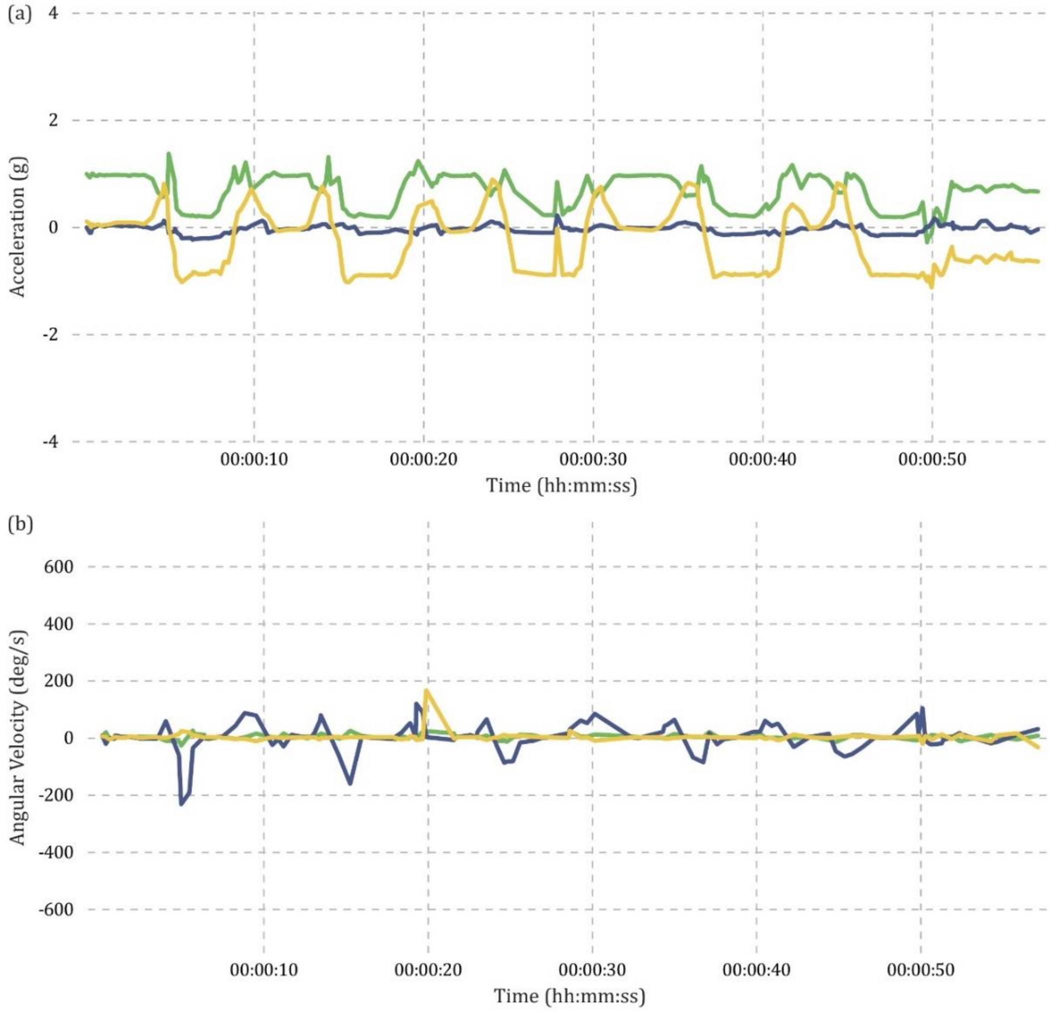

Figure 3.43 Data taken at the lower back for lying down. (a) Acceleration and (b) Angular velocity.
x-axis, y-axis and z-axis.

Figure 3.43a shows acceleration data that is similar to the acceleration data for sitting on a chair seen in Figure 3.27b, there is an increase in the z-axis and x-axis as the participant is lying done. Additionally, after the increase in the z-axis and x-axis, there is a decrease to below the standing level as the participant is lying down. Unlike for the waist, the z-axis and x-axis are not inverted and unlike the chest, both the z-axis and x-axis are at a different level while the participant is lying down. Figure 3.43b shows the gyroscope data of the lower back, which like the chest and waist is the same pattern as sitting on a chair (shown in Figure 3.27b).

The graphs for the falling activity, depicted below in Figure 3.44 - Figure 3.46, have the most unique pattern compared to any of the other activities seen so far. This was because there was a large change in the acceleration in the y-axis and there were changes in the angular velocity in both the z-axis and y-axis, which was only previously seen during turning activities.

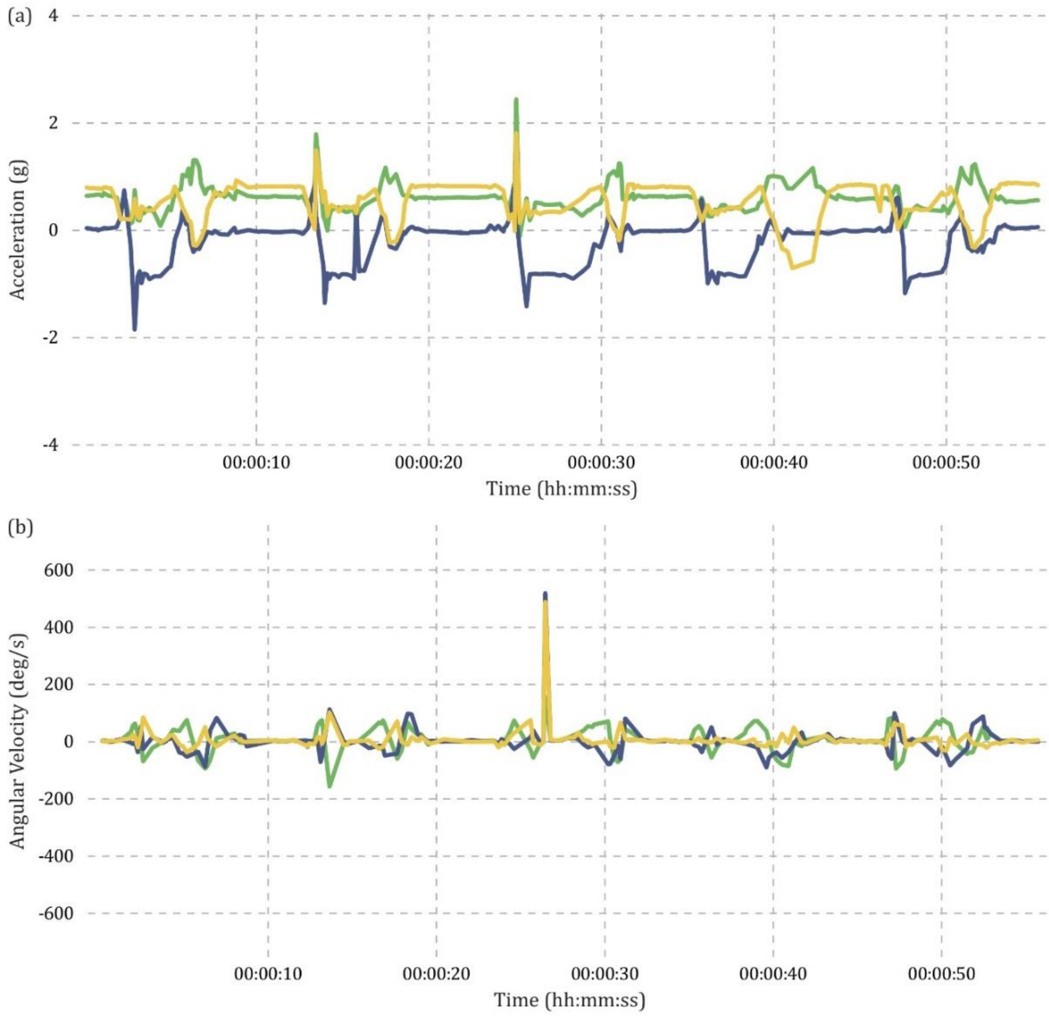

Figure 3.44 Data taken at the chest for the fall. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.44a shows a decrease in acceleration in the y-axis as the point of fall and a slight decrease in the acceleration in the z-axis and x-axis. For the second and third falls, the graph shows a large spike in acceleration on the z-axis and x-axis, which then drops back down. Whilst the participant is lying down, the acceleration in all three axes was fairly stable and as the participant raised again there is an increase in the acceleration in all axes. The acceleration follows the pattern seen in other activities when the participant returned to a standing position, as seen in Figure 3.23a and Figure 3.41a. The gyroscope data showed a change in the angular velocity in the y-axis that followed the same pattern as seen in Figure 3.23b however, there was also a change in the angular velocity in the z-axis and x-axis in this case. The z-axis showed a decrease and then an increase in angular velocity at the point of fall and as the participant stands. The x-axis changes are the inverse of the z-axis.

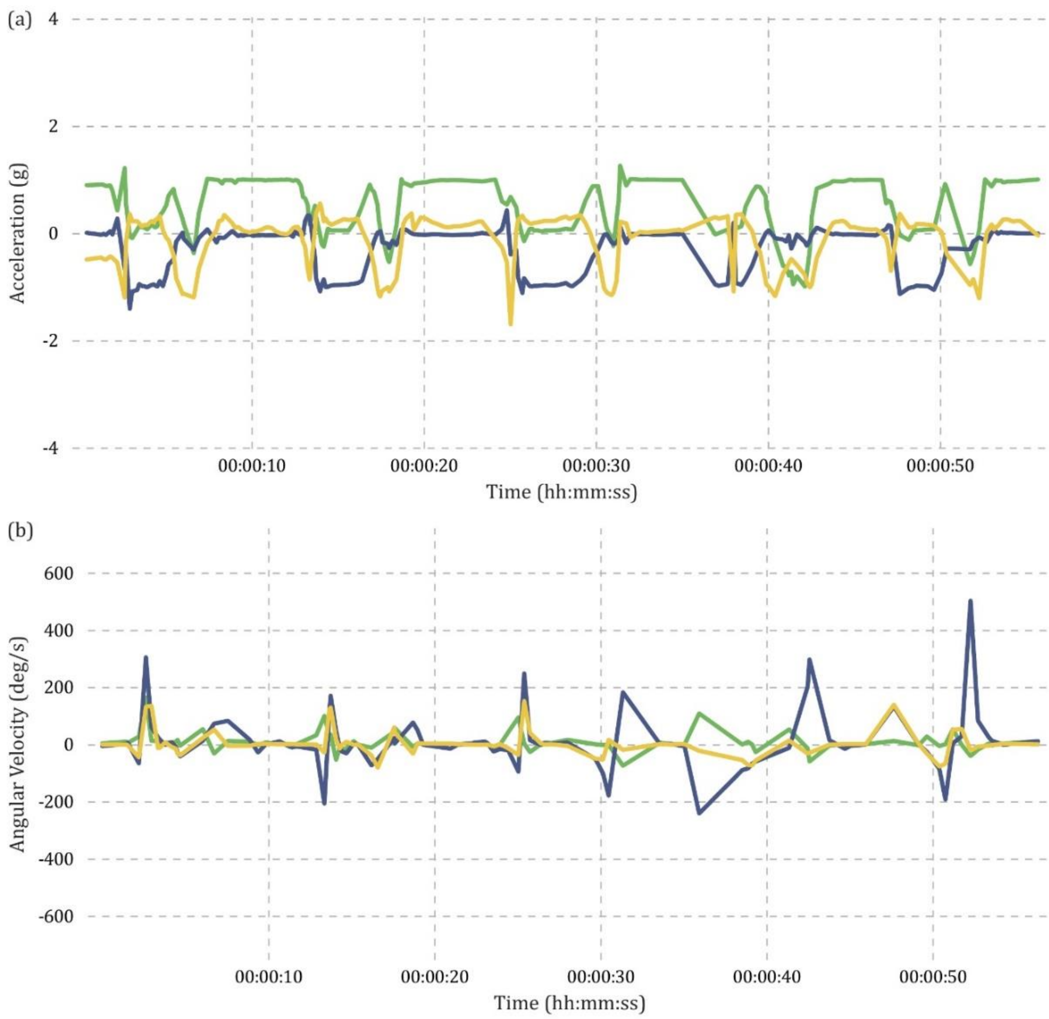

Figure 3.45 Data taken at the waist for the fall. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.45a also showed a large decrease in the acceleration in the y-axis at the point of fall, as well as an increase and decrease in both the z-axis and x-axis. As the participant returned to a standing position there was an increase in the y-axis acceleration, a decrease followed by an increase in the z-axis and an increase, decrease, and then increase in the x-axis acceleration. The gyroscope data shown in Figure 3.45b followed the same pattern described above for Figure 3.44b.

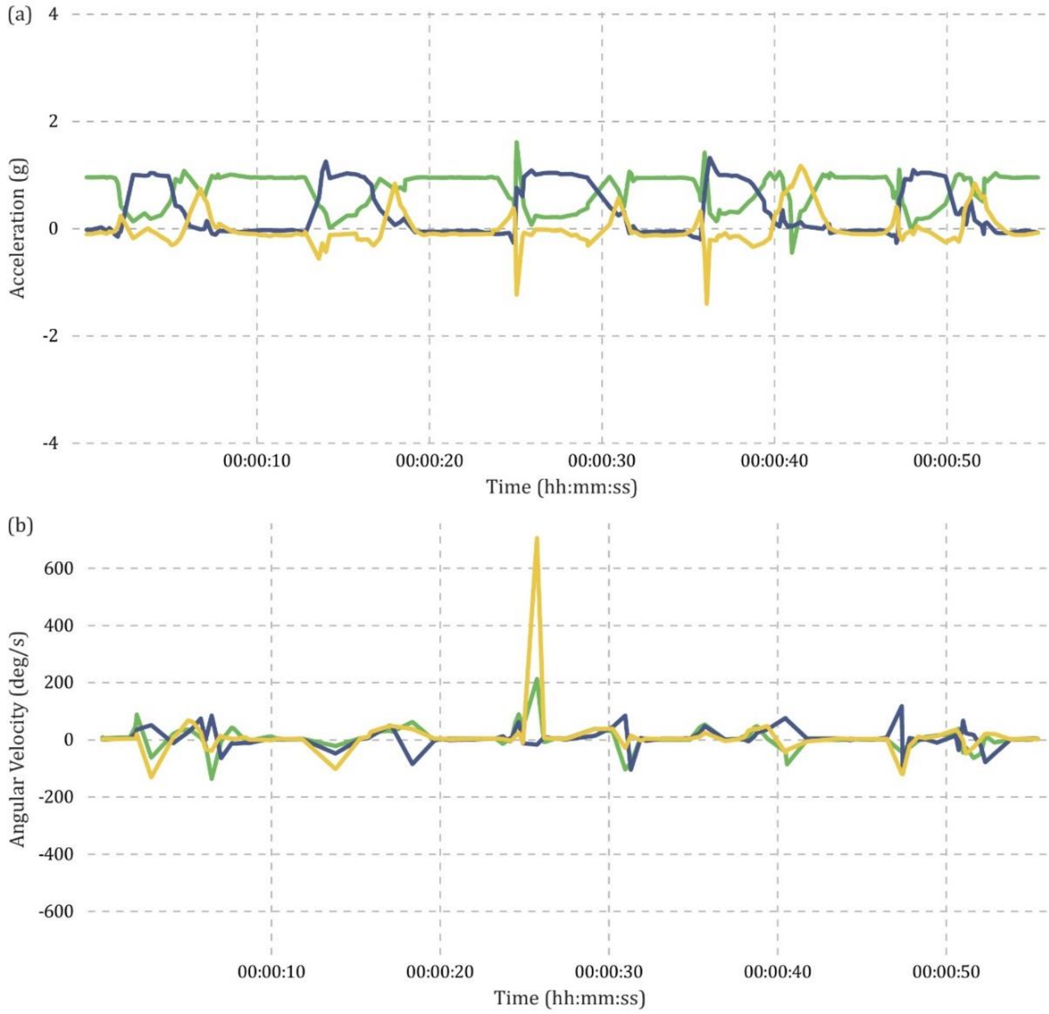

Figure 3.46 Data taken at the lower back for the fall. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.46a showed the acceleration data for the falling activity with the tracker on the lower back. Like in Figure 3.44a and Figure 3.45a, there was a large change in the acceleration in the y-axis at the point of fall, for the lower back this was an increase, and there was a decrease in the x-axis acceleration. The acceleration in the z-axis only had a small change compared to the x-axis. However, as the participant stood up there was a clear, significant increase in the z-axis acceleration. The x-axis also increased as the participant stood, while there was a decrease in the y-axis acceleration. Additionally, the gyroscope data did not show clear patterns, the angular velocity in the y-axis tended to follow the patterns described for the sitting ADLs. There were also changes in the angular velocity on the x-axis and z-axis, however, this appeared to be inconsistent.

3.3.2.5 SUMMARY

Walking can be seen in the acceleration and gyroscope data, however walking slowly is much harder to distinguish from standing still in the acceleration. As the participant moves slower, the changes in acceleration were smaller. The gyroscope data shows the turns for both walking and walking slowly. Like with the thigh, the sitting on a chair and sitting on the stool activities look the same for each of the three locations presented above. The waist had the largest changes in acceleration in the x, y and z-axes. Kneeling had a similar pattern to the sitting on a chair and sitting on a stool activities, but the acceleration data behaved slightly differently. As for the sitting ADLs, both for lying down and falling, the lower back has the smallest changes in acceleration.

Whilst the experiments were performed it became obvious that the chest is not the most appropriate placement for a sensor for women as the tracker flipped around for most participants and needed readjusting. Additionally, during the experiments the lower back tracker did not work for two participants and the chest did not work for one participant. The waist tracker stopped working during the activities for one participant. As the waist and lower back tracker gave similar results, and the lower back tracker disconnected on two participants, the waist was chosen for the validation experiments performed later.

3.3.3 Ankle

3.3.3.1 Walking

Figure 3.47 and Figure 3.48 show the accelerometer and gyroscope data taken at the ankle, for walking and walking slowly respectively.

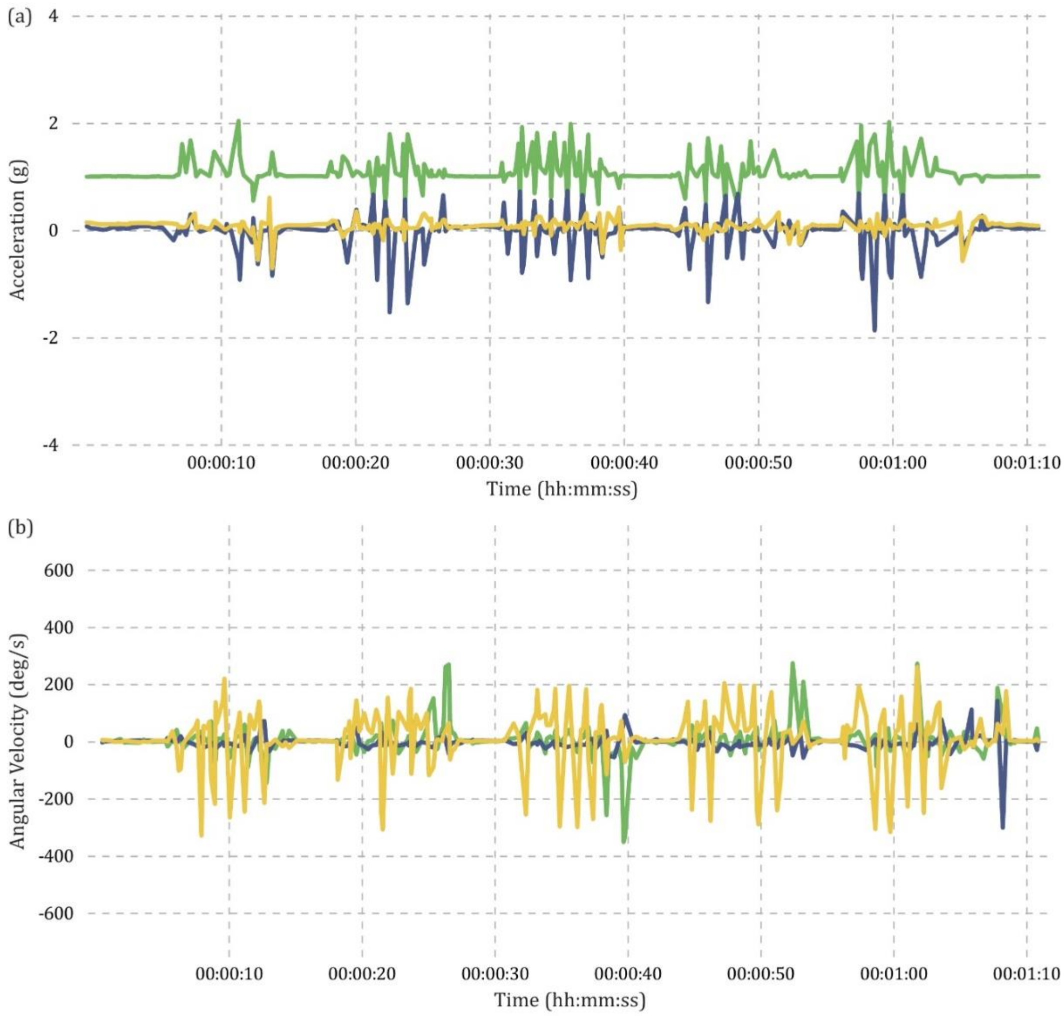

Figure 3.47 Data taken at the ankle for the walking activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

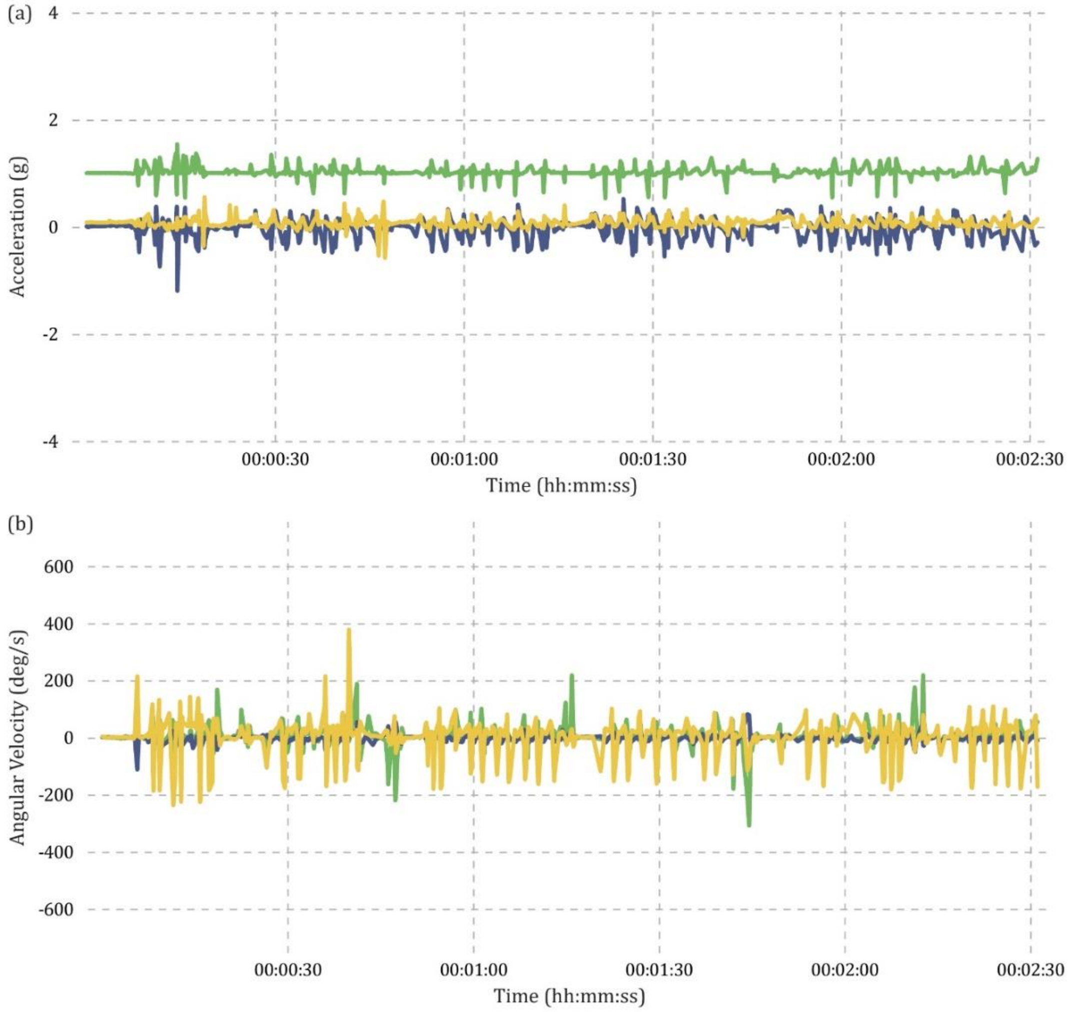

Figure 3.48 Data taken at the ankle for the walking slowly activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

In Figure 3.47 and Figure 3.48, the five repeats of walking can clearly be seen compared to standing still in both the accelerometer and gyroscope data. The major difference between both sets of data is that slow walking has smaller changes in acceleration and angular velocity.

3.3.3.2 Sitting ADLS

The sitting ADLs; sitting on a chair (Figure 3.49), sitting on a stool (Figure 3.50) and kneeling (Figure 3.51) are presented together below.

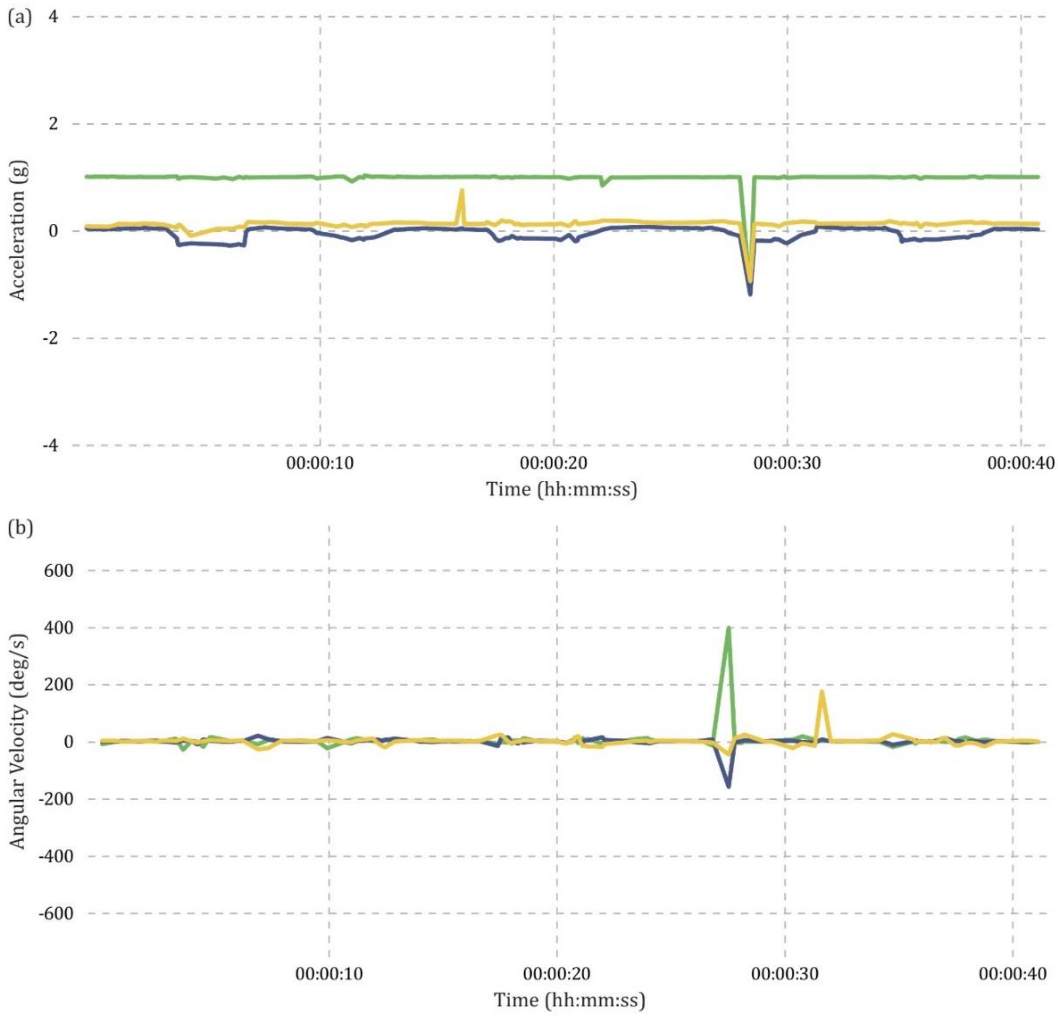

Figure 3.49 Data taken at the ankle for sitting on a chair. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

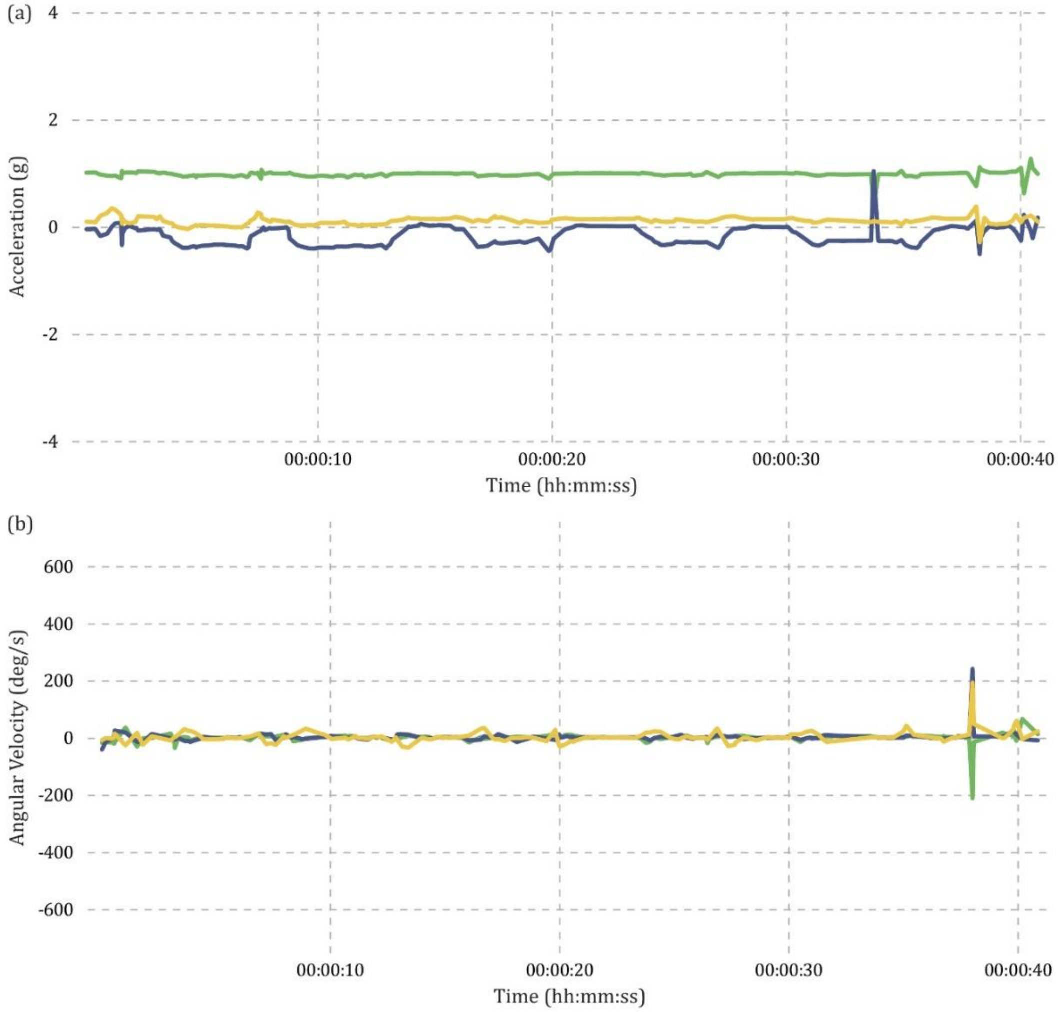

Figure 3.50 Data taken at the ankle for sitting on a stool. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Both sitting on a chair seen in Figure 3.49 and sitting on a stool shown in Figure 3.50 showed similar patterns. In the acceleration data, a small decrease was evident in the y-axis for both activities, however, Figure 3.50a had a larger visible decrease in the y-axis for acceleration. This was due to the participant having to travel further to sit on the stool. The angular velocity in Figure 3.49b and Figure 3.50 showed some changes with the greatest difference seen in the z-axis. As the change in angular velocity was so small compared to the other locations discussed previously, is it unclear if there is a pattern.

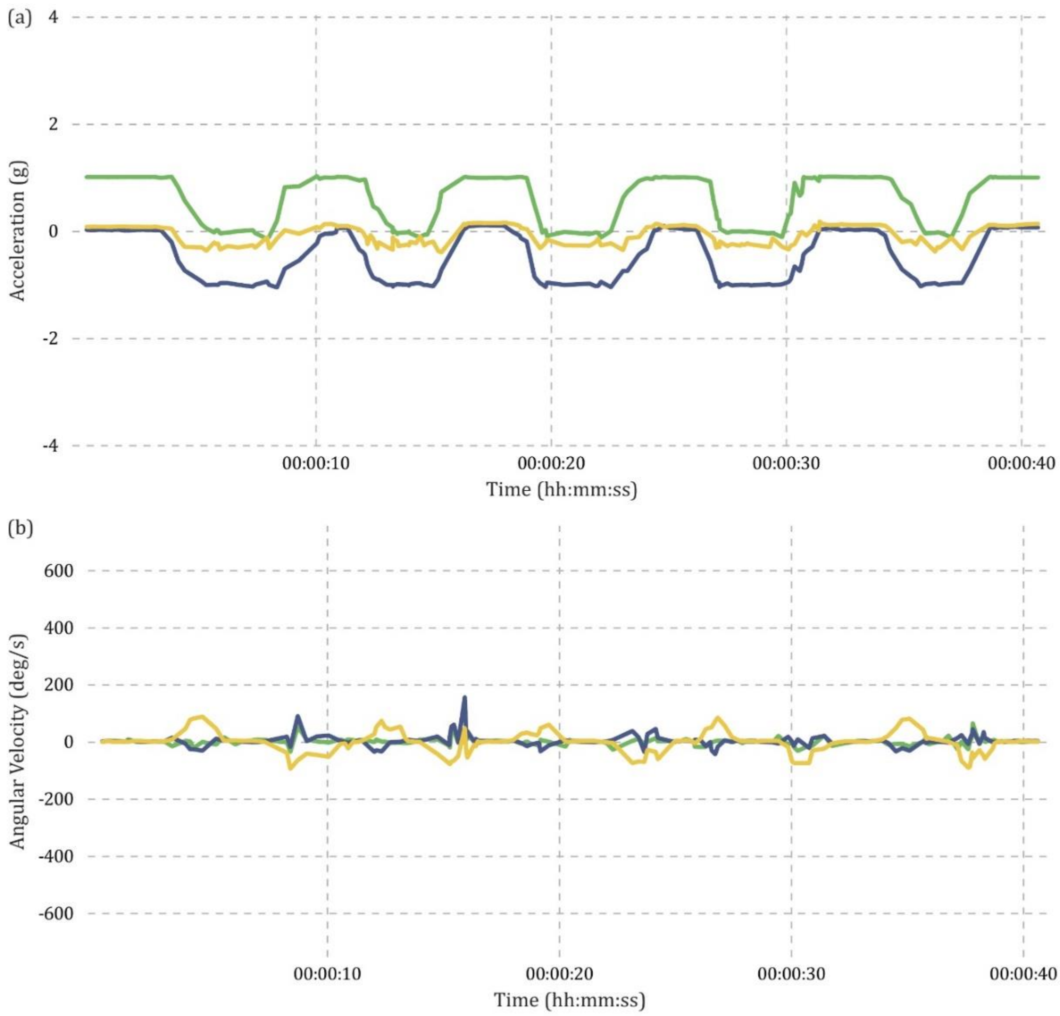

Figure 3.51 Data taken at the ankle for the kneeling activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.51a showed the acceleration data and like in Figure 3.49a and Figure 3.50a where there was a decrease in the y-axis as the participant kneeled. Additionally, there was a decrease in the x-axis and a slight decrease in the z-axis, not seen in the other sitting ADLs. Figure 3.51b showed the change in angular velocity as the participant kneeled and got back up. Unlike the other sitting ADLs, there was a visible change in the pattern in the z-axis, showing an increase in the angular velocity whilst kneeling and a decrease as the participant returned to a standing position. There was also a change in the angular velocity in the x-axis and y-axis which were smaller than the z-axis and appeared to move in the opposite direction.

3.3.3.3 OTHER ADLS

The other ADLs; reaching high to low, Turn 180^0' and 'Timed Up and Go' are presented in Figure 3.52, Figure 3.53 and Figure 3.54 respectively.

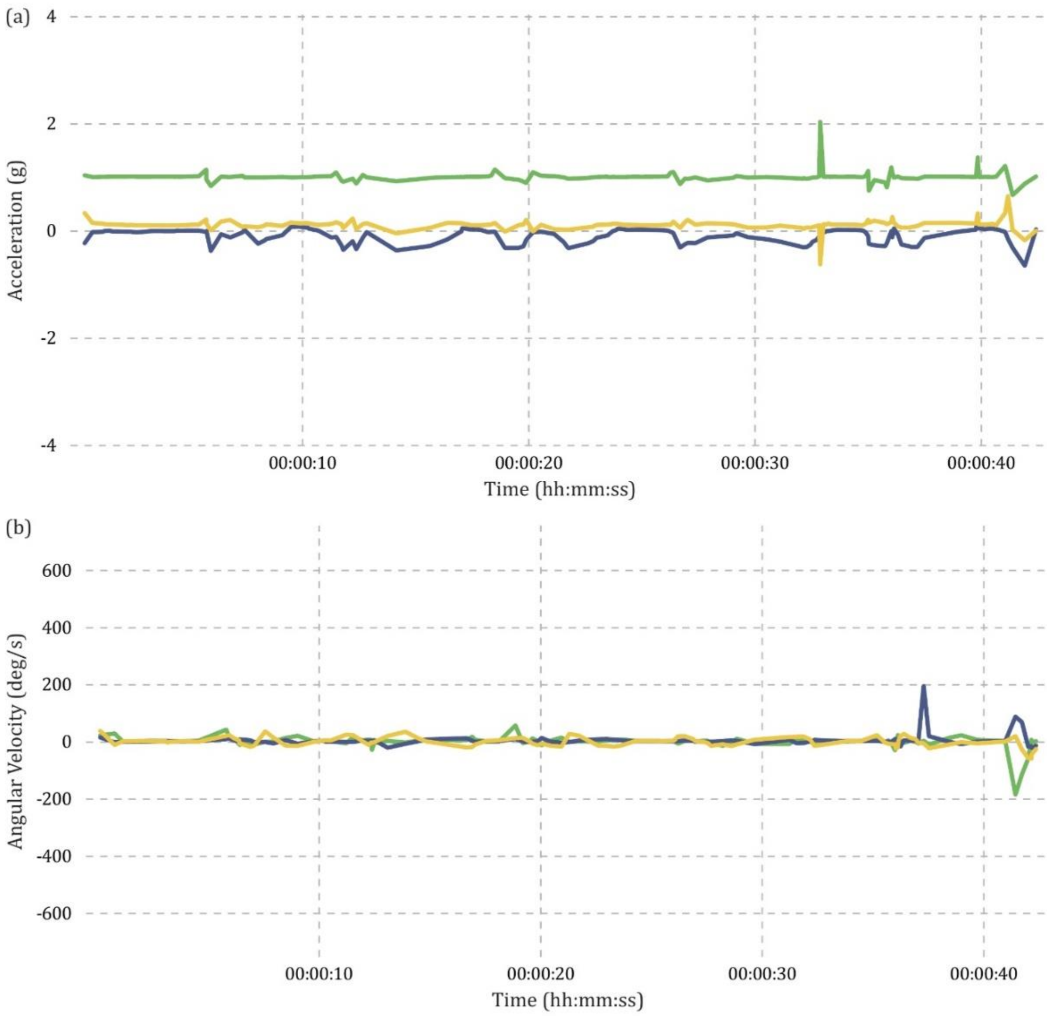

Figure 3.52 Data taken at the ankle for reaching high to low. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

During the reaching high to low activity, there was limited movement in the feet, and this was apparent in Figure 3.52, with the acceleration data being fairly consistent as the participant moves onto their toes and puts their feet back down to bend to touch the floor. Similarly, in Figure 3.52b, there was minimal change in the angular velocity during this activity.

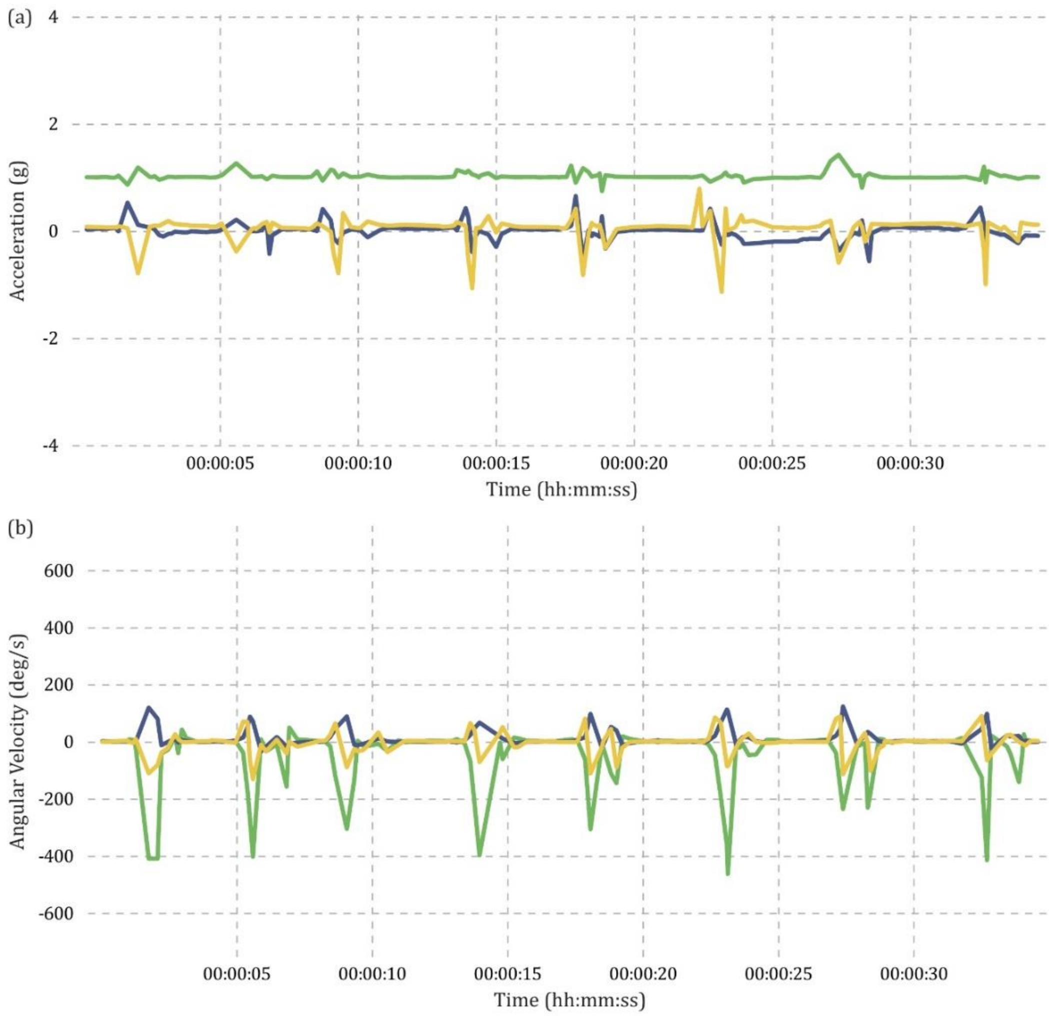

Figure 3.53 Data taken at the ankle for the turning activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.53a showed a decrease in acceleration in the z-axis as well as an increase in the y-axis, and some change in the acceleration in the x-axis for each turn. Figure 3.53b followed the same pattern as seen for the other sensor locations discussed previously. There was a large decrease in the x-axis as the participant turned, this change in angular velocity was the largest for the ankle compared to other sensor locations. There was also a decrease in the angular velocity on the z-axis and an increase in the y-axis as the participant turned.

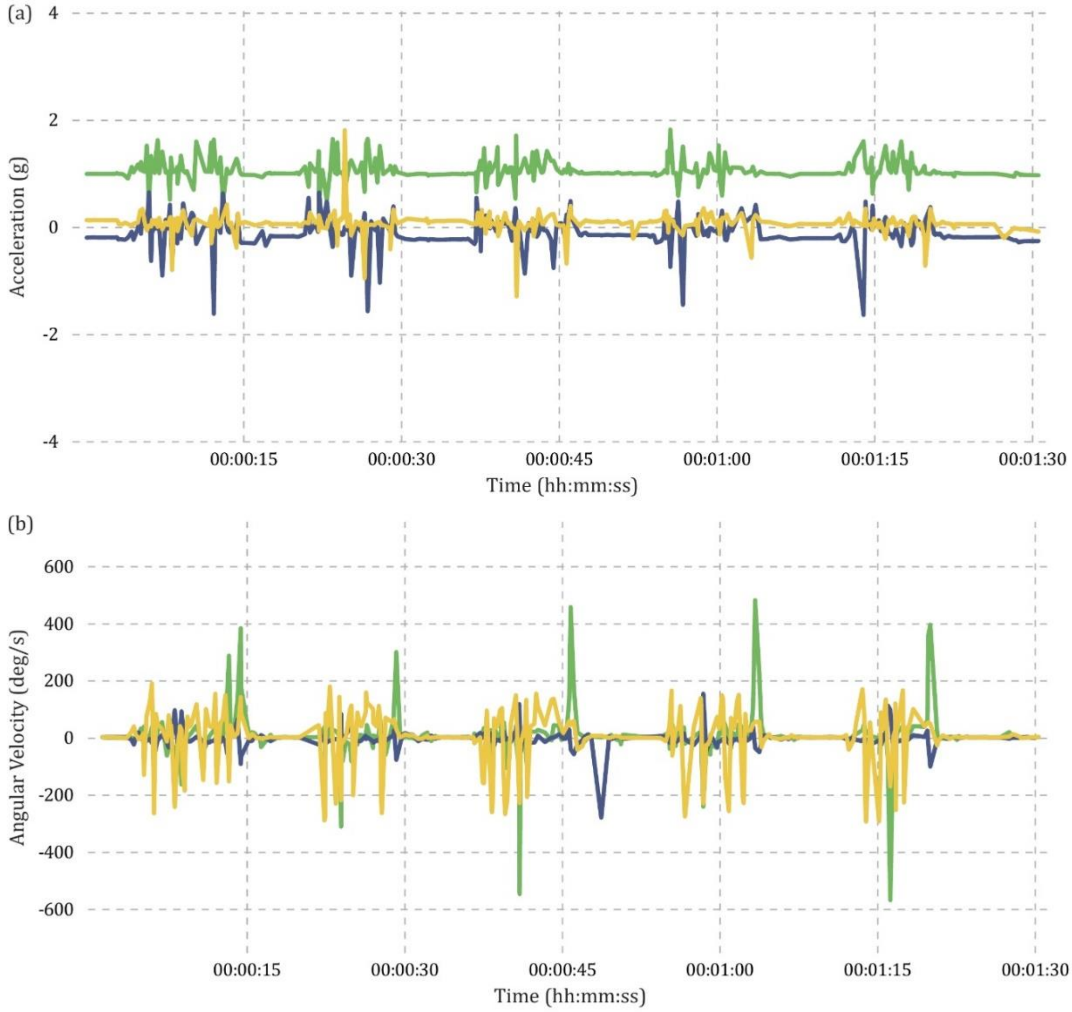

Figure 3.54 Data taken at the ankle for the 'Timed Up and Go' test. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.54a was similar to Figure 3.47a (walking activity). The walking activity masks any acceleration changes that occur whilst the participant stood up or sat down as these elements were small by comparison (see Figure 3.49). This was the case for Figure 3.54b, except the turn in the middle and at the end of the activity can be seen in most of the repeats.

3.3.3.4 LYING DOWN AND FALLING

Figure 3.55 and Figure 3.56 present the data taken at the ankle for lying down and falling.

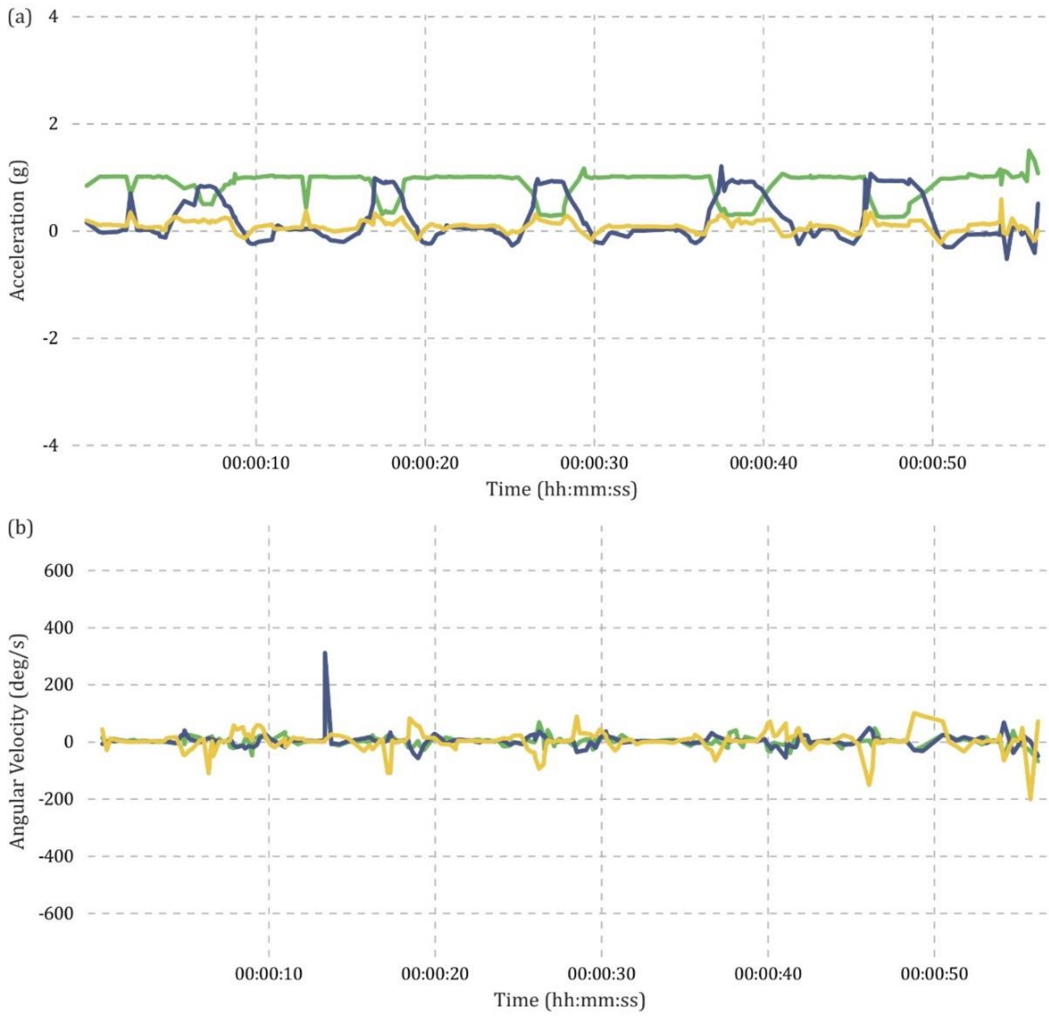

Figure 3.55 Data taken at the ankle for lying down. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.55a shows the change in acceleration as the participant stood, laid down and returned to a standing position. As the participant laid down there was an increase in the y-axis acceleration, a decrease in the x-axis and a smaller increase in the z-axis, which was reversed as the participant got back up. Figure 3.55b showed a decrease in the z-axis angular velocity as the participant laid down and an increase as they returned to a standing position. The angular velocity in the x-axis and y-axis changed during the activity, however, there is not a clear visible pattern.

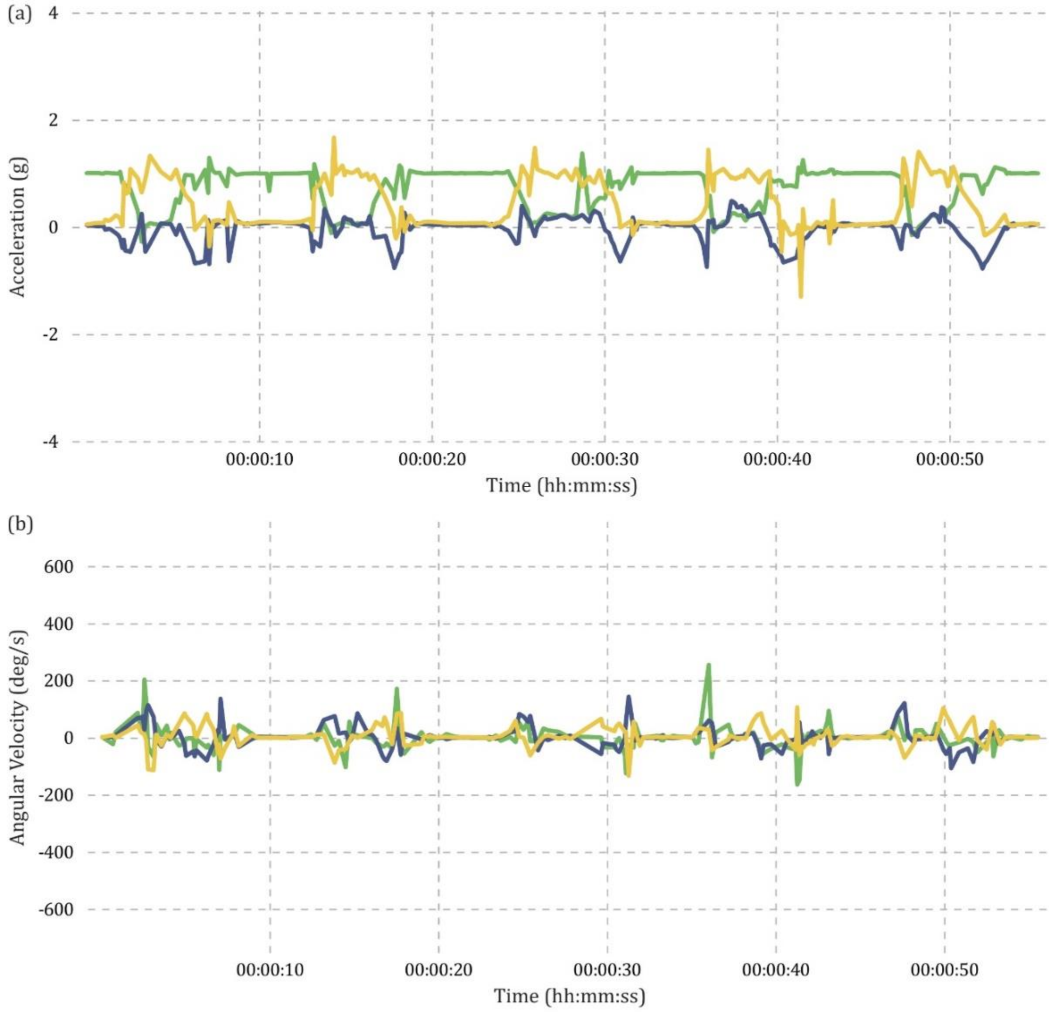

Figure 3.56 Data taken at the ankle for the fall. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.56a showed the changes in acceleration as the participant fell and got up again. There was a decrease in the x-axis acceleration, like there was when the participant laid down and an increase in the z-axis, which was much larger than for lying down and due to the participant's acceleration, more for the fall. There was also a change in the y-axis acceleration, but this did not show a consistent pattern. Figure 3.56b showed the change in the angular velocity during the activity, but there was no consistent pattern observed for each fall.

3.3.3.5 SUMMARY

The walking activities (Figure 3.47 and Figure 3.48) show the largest change in acceleration compared to the other locations. In addition, sitting on a chair and sitting on a stool show smaller changes in acceleration. These results are unlike the thigh and centre of gravity locations. This is because the ankle shows foot movement more. In the sitting ADLs the foot only moved during the kneeling activity, it was mostly still otherwise. This is reflected in the results. Also, the turning activity has the greatest change in angular velocity compared to the other locations.

3.3.4 WRIST

3.3.4.1 WALKING

Figure 3.57 and Figure 3.58 show accelerometer and gyroscope data for walking and walking slowly respectively.

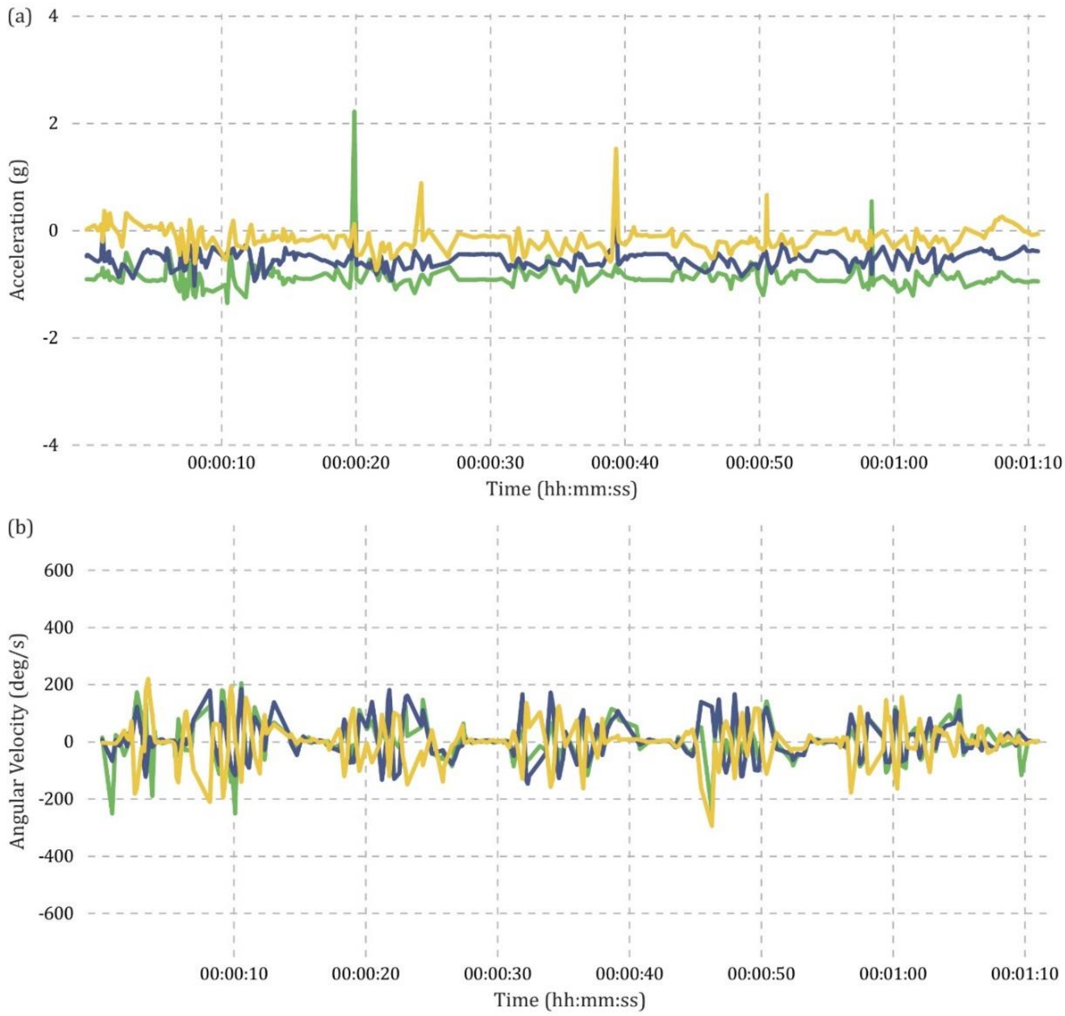

Figure 3.57 Data taken at the wrist for the walking activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

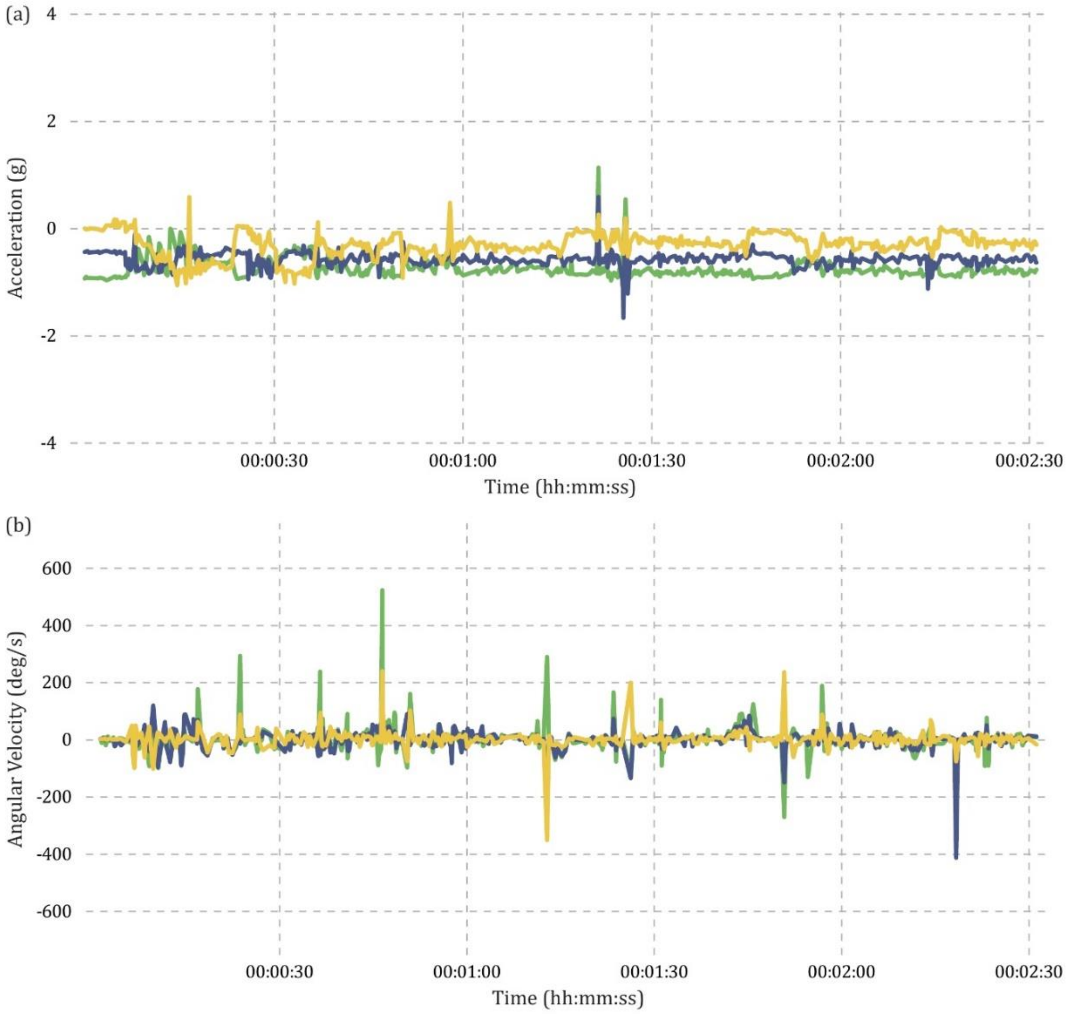

Figure 3.58 Data taken at the wrist for the walking slowly activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

In Figure 3.57, the acceleration and gyroscope data show the five repeats of the activity, as can be seen for all the other locations. Walking slowly has smaller changes in acceleration and angular velocity than walking as there was less arm movement. Additionally, it is not always clear where the participant is standing still, probably due to small arm movements while standing still.

3.3.4.2 SITTING ADLS

Figure 3.59, Figure 3.60 and Figure 3.61 present the three sitting ADLs, sitting on a chair, sitting on a stool, and kneeling respectively.

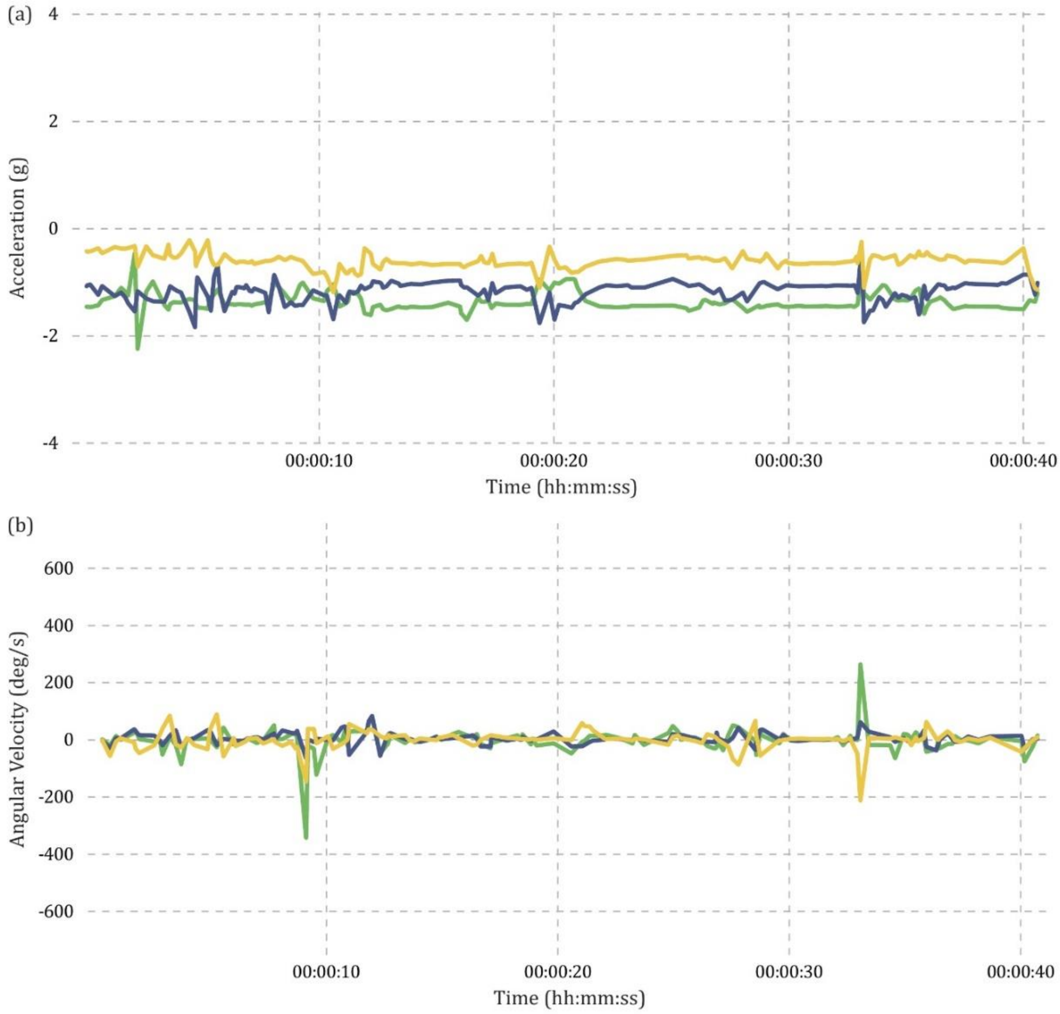

Figure 3.59 Data taken at the wrist for sitting on a chair. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

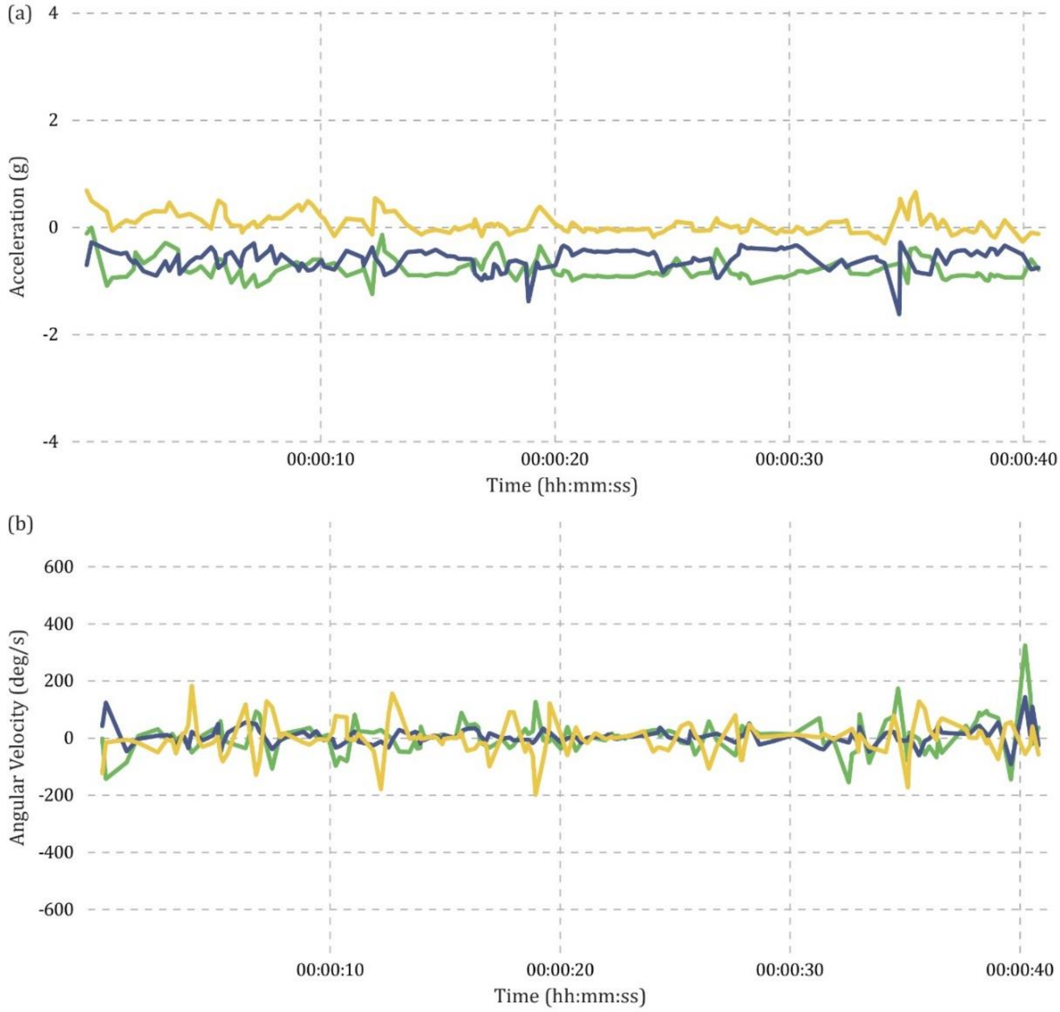

Figure 3.60 Data taken at the wrist for sitting on a stool. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

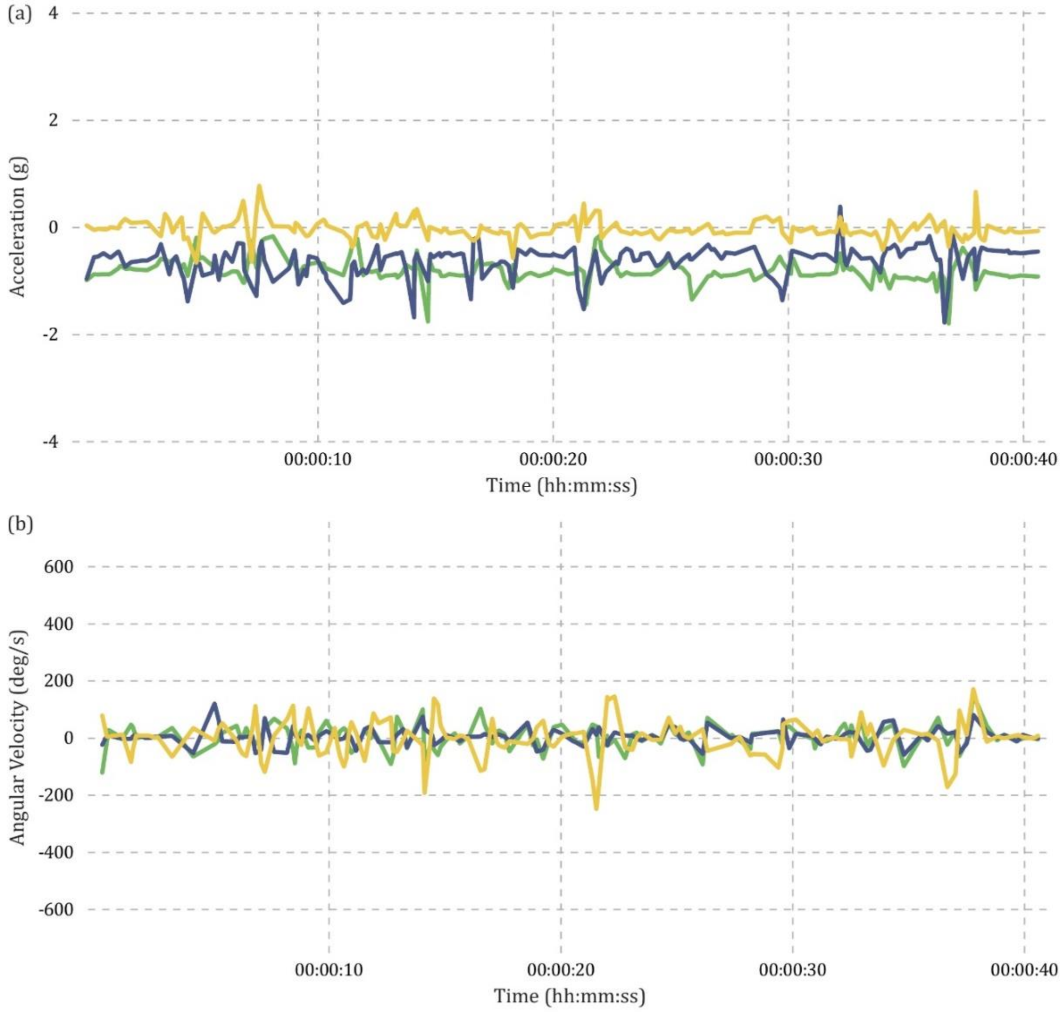

Figure 3.61 Data taken at the wrist for kneeling activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

For all the 'sitting' ADLs both the accelerometer data and gyroscope data showed no obvious patterns for when the participant was standing or sitting (or kneeling). Additionally, it was not easy to ascertain when the participant was standing still between each repeat in the data.

3.3.4.3 OTHER ADLS

Figure 3.62, Figure 3.63 and Figure 3.64 present the accelerometer and gyroscope data for reaching high to low, 'Turn 180^0' and 'Timed Up and Go' respectively.

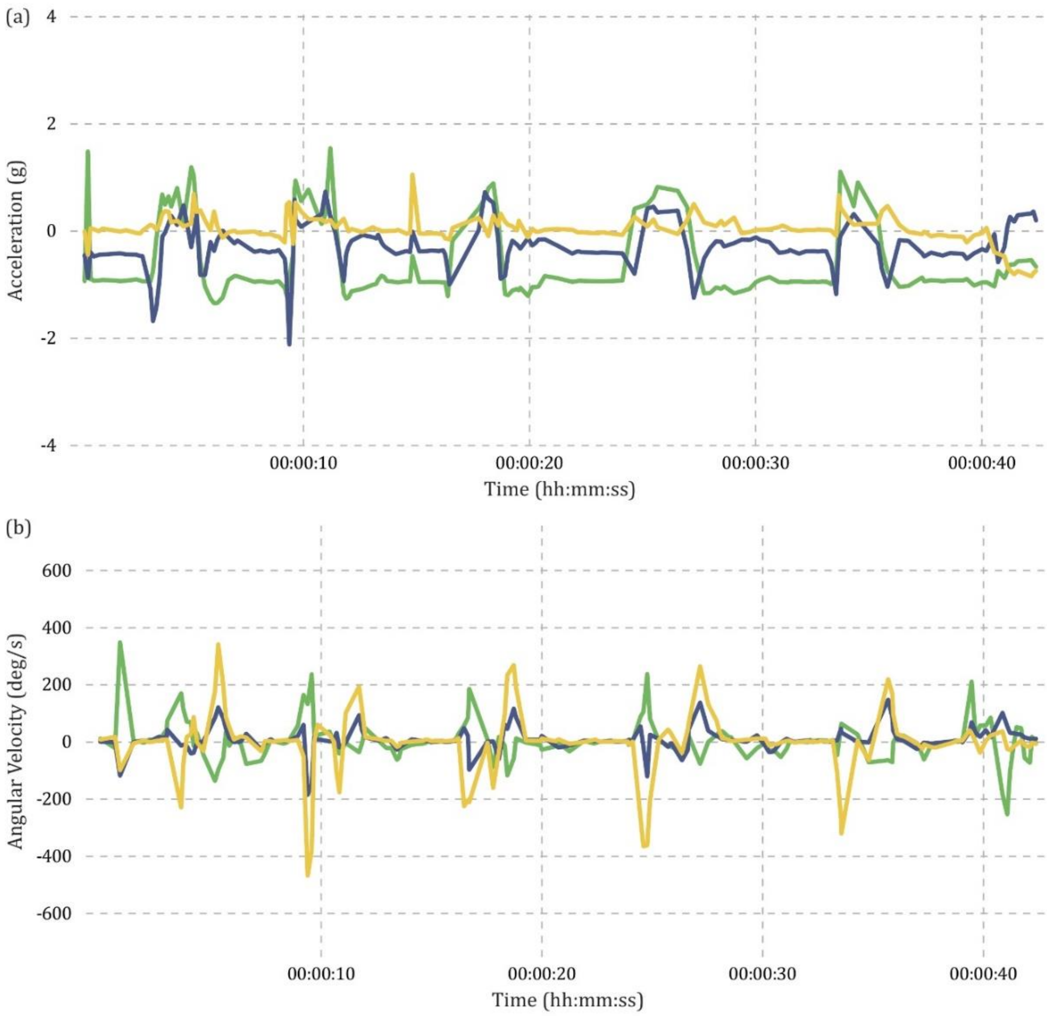

Figure 3.62 Data taken at the wrist for reaching high to low. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.62a showed the acceleration at the arm when the participant reached up and down. There was a decrease in the y-axis acceleration as the arm reached up, and this increased as the arm moved down to the ground, and decreased again as the arm returned to its original position. There was an increase in the acceleration in the x-axis as the arm moved and a decrease once it return to its original position. There was also a change in the z-axis acceleration, however, this was much smaller and did not present a clear pattern. Figure 3.62b showed an increase in the angular velocity in the x-axis at the start of the activity, a decrease as the participant reached down, and no change in angular velocity as the arm stays still. The change in the angular velocity observed in the z-axis and the y-axis was the opposite of the x-axis. The changes in angular velocity in the z-axis were larger than the x-axis and y-axis.

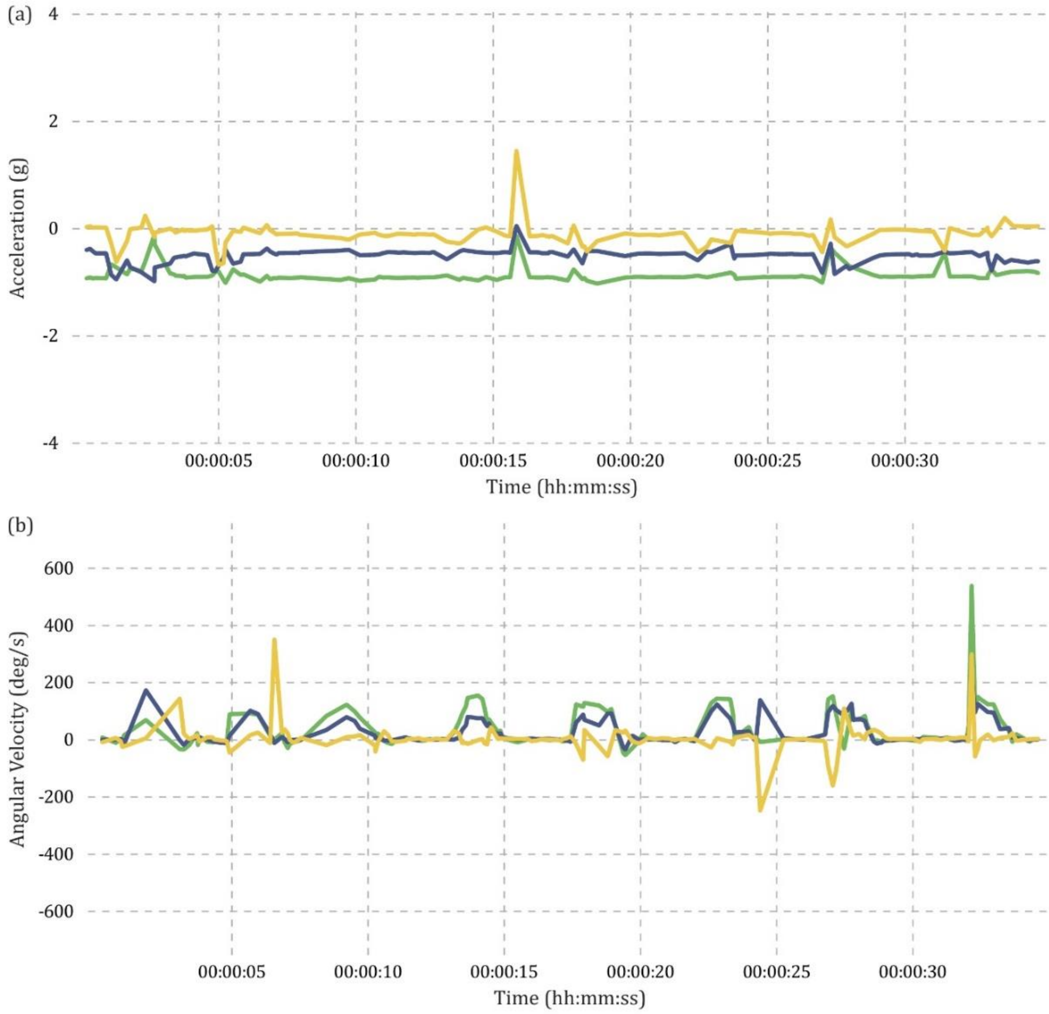

Figure 3.63 Data taken at the wrist for the turning activity. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

There were no patterns in the acceleration data seen in Figure 3.63a. This is consistent with all the other sensor locations except for the ankle. Figure 3.63b showed the change in angular velocity as the participant turned. There was an increase in the x-axis and y-axis angular velocity, as well as a small change in the z-axis.

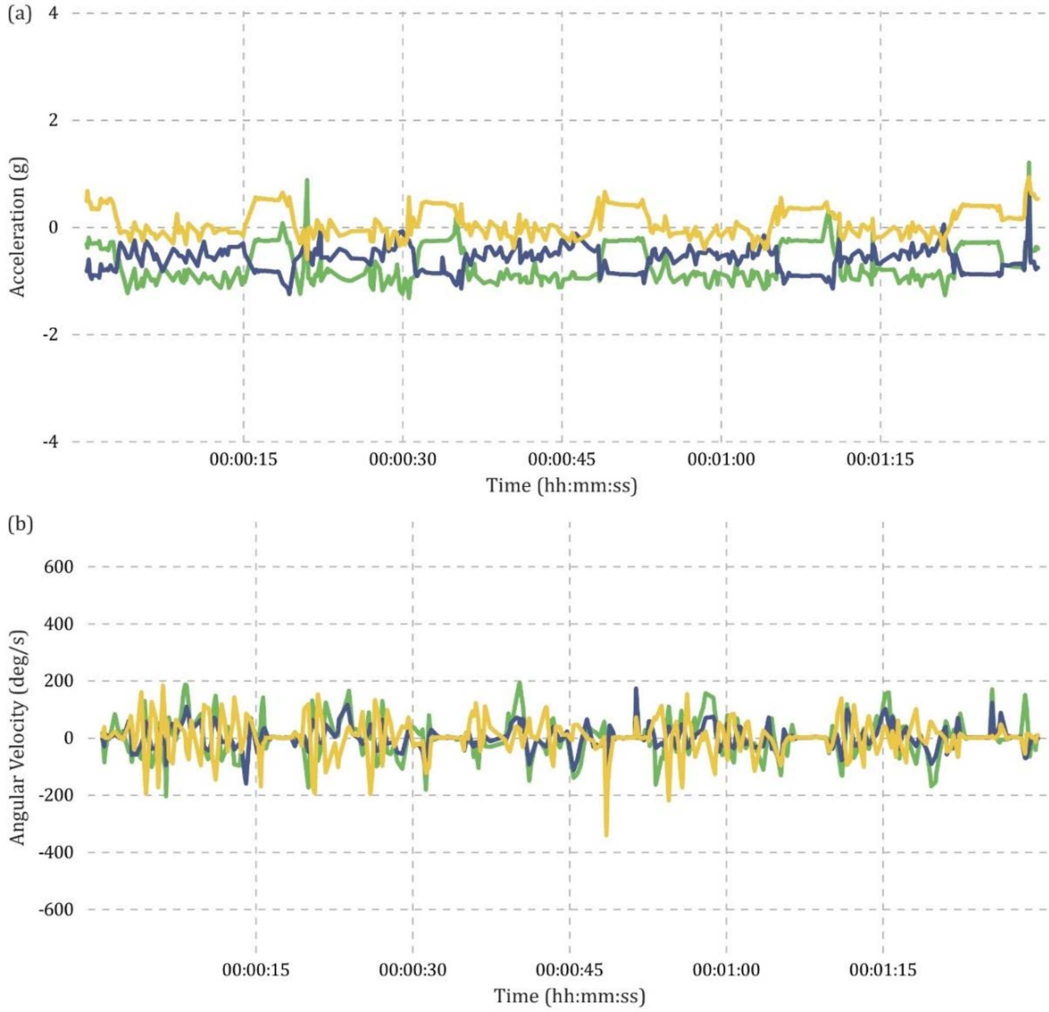

Figure 3.64 Data taken at the wrist for the 'Timed Up and Go' test. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

Figure 3.64a is similar to the data for walking, yet shows no change in the acceleration as the participant is sitting still. Figure 3.64b, is the gyroscope data of the 'Timed Up and Go' test. This is similar to the data observed for walking. However, there it is visible when the participant is sitting still, as the angular velocity is 0.

3.3.4.4 Lying Down and Falling

Figure 3.65 and Figure 3.66 present the data taken at the wrist for lying down and falling.

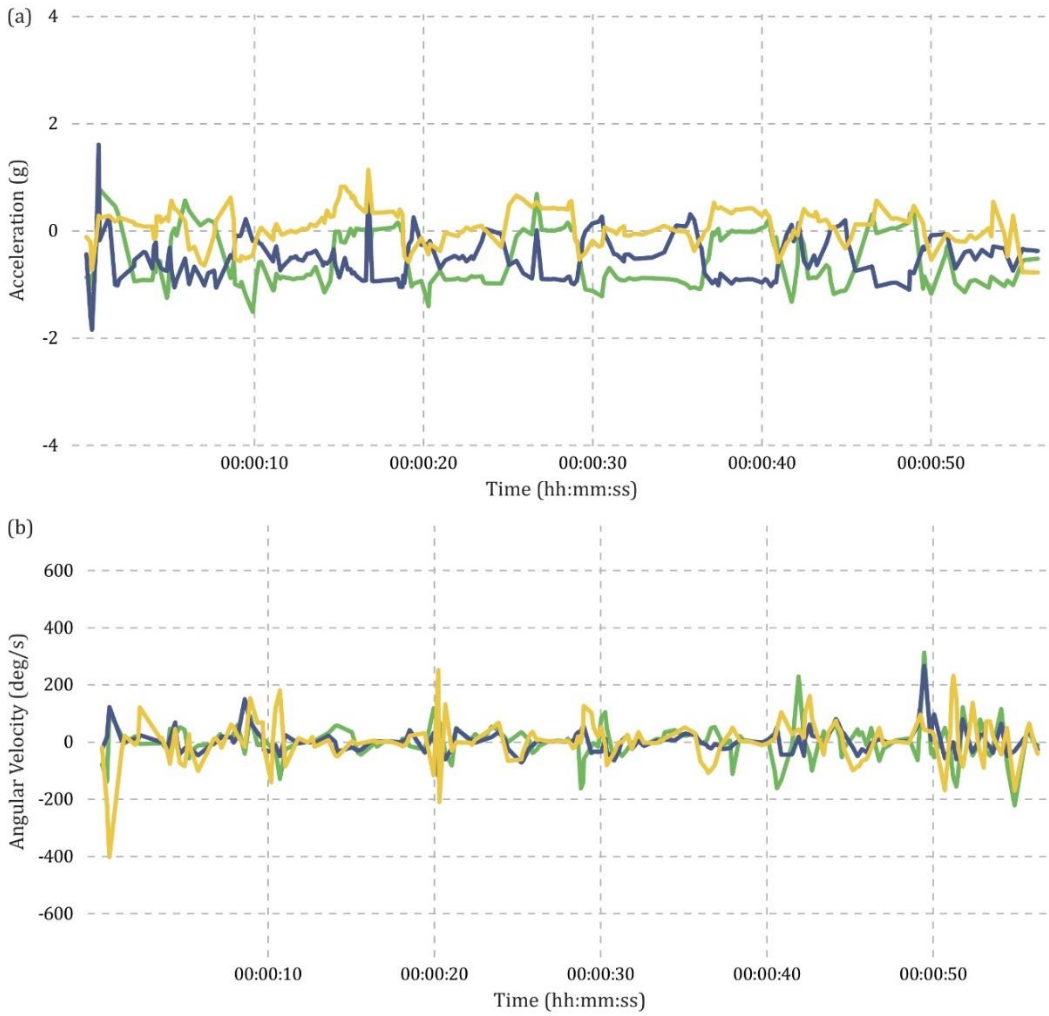

Figure 3.65 Data taken at the wrist for lying down. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

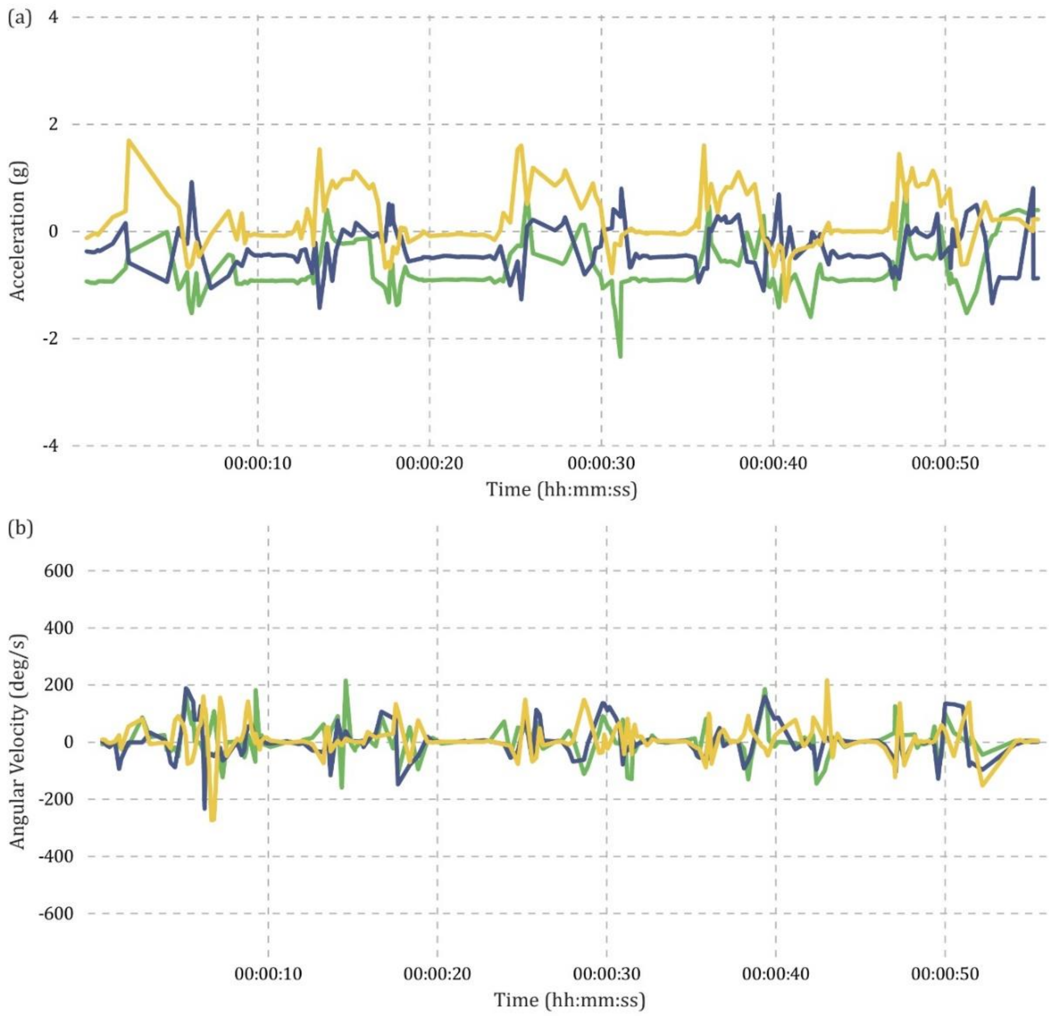

Figure 3.66 Data taken at the wrist for the fall. (a) Acceleration and (b) Angular velocity. x-axis, y-axis and z-axis.

The acceleration data for both lying down, Figure 3.65a, and falling, Figure 3.66a have a similar pattern: An increase in the z-axis and x-axis and a decrease in the y-axis acceleration was observed. The participant standing still between activities was clearer in the falling activity data than it was for lying down data; this was due to the change in acceleration being larger during the falling activity. The gyroscope data for both the falling activity (Figure 3.66b) and the lying down activity (Figure 3.65b) showed no obvious pattern, however again it was clearer when the participant is standing still between falls rather than lying down (this is because the change in angular velocity was much larger during the falling activity).

In comparison to all of the other locations, the wrist showed the least amount of information. This made it harder to determine between the different ADLs and fall events. As these experiments were conducted in a lab setting the participants tried not to move their arms too much: in a real-world scenario, arm movements would make it very difficult to classify between ADLs and near-falls.

3.3.4.5 Summary

The wrist data shows that the activities with the clearest patterns are walking, reaching high to low, turning and falling. However, walking became difficult to distinguish from standing still if the participant was walking slowly. These results are due to the unconscious movement of the arms during most of the activities.

3.4 Discussion

The walking activities were visible for all locations, but the pattern is not easy to describe. Walking from a wrist-worn sensor was the hardest to identify as there was a lot of movement at the wrist even when the participants were standing still. The participants were instructed to stand as still as possible between each repeat to help identify each repeat.

Of the three sitting ADLs, sitting on a chair and sitting on a stool had very similar patterns for the thigh, chest, waist, lower back and ankle. There was a larger acceleration change for sitting on a stool compared to sitting on a chair for the chest, waist, lower back, and ankle. This was due to the fact that the stool was lower down than the chair, so there was a longer drop resulting in a larger acceleration. Kneeling at the thigh had a different pattern as the movement of the thigh for the kneeling activity is different to the chest, waist, lower back and ankle. For the ankle, the kneeling activity showed the same pattern as the other sitting ADLs except with a much larger change in acceleration. For the chest, waist and lower back, the kneeling activity showed a similar pattern to the other sitting ADLs.

The wrist was the only sensor location where the full high-to-low activity could be clearly identified. This was because the left wrist, which has the tracker attached to it, was the arm that was used for the high-to-low movement. The other locations only showed when the participant bent low during the activity. This was most likely because there was limited movement as the participant was on their toes.

During the turning activity, all of the sensor locations showed the turn in the gyroscope data. The ankle had the largest change in angular velocity as well as a clear change in acceleration. The thigh also shows a change in the acceleration for each turn; however, this was much smaller than at the ankle. Additionally, only the ankle showed the turn in the accelerometer data during the walking activity: This can be seen in Figure A.25 (‘Timed Up and Go’ validation dataset).

The ‘Timed Up and Go’ test showed a combination of sitting on a chair, walking, and turning activities. This was most clear in the thigh data, but can also be seen in the chest, waist and lower back. As the acceleration changes at the ankle when sitting on a chair were very small, this could not be clearly identified in the accelerometer data of the ‘Timed Up and Go’ test.

For the thigh, chest, waist and lower back, lying down and falling showed similar patterns, in the acceleration data. During the fall activity, there was a larger change in acceleration in the x-axis and z-axis, as well as a large change in acceleration in the y-axis that is not seen in the acceleration data for lying down, as they performed these activities in different directions. This was the same for the data taken at the ankle, but rather than the y-axis, it was the z-axis acceleration that did not change when the participant laid down but did when they fell. At the wrist, the pattern for lying down was not as clear, or consistent between the repeats. However, the pattern for falling was clearer as the changes in acceleration were larger.

The study [22] discussed in Section 3.1 found that the waist and the thigh provide the most accurate results for fall detection. The results from this paper do align with the results found for falls presented in this chapter.

The other participant data in Appendix A.3 Other Participant Data was in agreement with participant one data shown in Sections 3.3.1 - 3.3.4. Generally speaking, data was consistent between participants. However, as the trackers did not measure with a consistent sampling rate some information was lost. The inconsistent sampling rate made it impossible to quantify the data using the methods described in the paper [28]. The method used the equation below to measure the total acceleration.

$$A_T = \sqrt{x^2 + y^2 + z^2} \qquad \text{Eq 3.1}$$

A_T is the peak, x is the acceleration in the x-axis, y is the acceleration in the y-axis and z is the acceleration in the z-axis. This was used to measure the variance, skewness, and kurtosis over a certain time interval. However, the calculations were not able to take into account the inconsistent sampling rate, which resulted in inaccurate statistics of the data. Additionally, as each participant attached the tracker to themselves, it was hard to quantify the data as the results are personal.

The validation data (presented in Appendix A.4 Validation Trials) was collected to confirm the data taken using the MetaTracker. This was because the sampling rate of the MetaTracker was inaccurate. The validation experiments used one MetaTracker at a time with the addition of the Bosch developmental kit at the thigh to test various sampling rates. As described in Section 3.2.5, only three of the locations were used and five of the activities were based on the original experiments. The original data was compared to validation data sets taken with the MetaTracker showing that the patterns previously observed were in agreement, validating the original datasets despite some gaps in the sampling. The sampling rate was more accurate when one tracker was used at a time. The validation experiments used the Bosch developmental kit, which always gave the correct sampling rate. Given the higher sampling rate this meant that even while the participant was still, there appeared to be large changes in the acceleration data due to the high sampling rate picking up very small movements by the participant. This was most problematic when looking at the walking activity, meaning that it was difficult to distinguish between when the participant was walking or still from the data. This showed that it would be best to use a lower sampling rate.

3.5 Conclusions

This work showed that all the explored sensor locations could be used for fall detection. This finding is in agreement with the literature, however, some locations allowed for falls and different ADLs to be more clearly identified.

The data showed that monitoring ADLs and falls at the wrist gave information that was least easy to interpret. The thigh showed the clearest patterns for most of the activities. The chest waist and lower back gave very similar data. Due to the issues with the chest and lower back trackers, the waist sensor ultimately gave the most reliable data. The ankle is best for monitoring the movement of the feet, as presented in the results section, which is beneficial for the detection of near-falls.

Having both the accelerometer and the gyroscope data was helpful to classify different activities and a 25Hz sampling rate is appropriate for detection. Ultimately this work showed that the fall/near-fall detection system should measure the acceleration, and ideally angular velocity, at the thigh, ankle, or waist.

Further work presented in Chapter 4, involved asking the intended users of the final E-textile their opinions to aid the development of prototypes. In addition, this pilot study has shown that other activities need to be studied once the final E-textile garment has been designed and made. Therefore, another human trial, presented in Chapter 5, was conducted to investigate stumbling (a type of near-fall), and three types of falls sideways, backwards and forwards using the final E-textile design. Stumbling was used to simulate near-falls, as it was easily performed in the room, did not require extra equipment and was safe. The additional falls were needed as people do fall in all directions and each produces different data.

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CHAPTER 4. DESIGNING E-TEXTILES FOR FALL AND NEAR-FALL DETECTION USING A HUMAN-CENTRED DESIGN APPROACH

ACKNOWLEDGEMENTS

The experimental work was conceived and conducted by Zahra Rahemtulla and Rachael Wickenden. The data interpretation was conducted by Zahra Rahemtulla.

Carlos Oliveira designed and produced the ankle and shorts prototypes. Eloise Slater designed and produced the patch prototype. Both were involved in the design sprint along with Zahra Rahemtulla and Rachael Wickenden.

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4.1 INTRODUCTION

This study contributes much-needed insight into what people over 65, specifically women, would or would not be willing to wear to monitor their risk of a fall. To understand the needs and preferences of the intended users, a Human Centred Design (HCD) approach was used. HCD focuses on the needs and wants of the users along with their experiences [1]. Usually, within the field of fall detection, the primary driving force is technology [2]. To the knowledge of the authors, there is no literature pertaining to human-centred design for fall or near-fall detection systems [3]. This study follows previous investigations into older women's clothing preferences [4,5], linking these preferences directly to the design of E-textile prototypes for near-fall detection.

Furthermore, there is limited research using HCD approaches within the field of E-textiles. This was acknowledged during the E-textiles conference held at Nottingham Trent University in November 2022. Salisbury *et al.* [6] discussed the benefits of working with end users for their insights into the perceived need for E-textile development and provides an example methodology and case study. Wang *et al.* [7] conducted interviews and questionnaires with people aged 60 and over. These were used to gain insight into their views on health, healthy ageing, healthcare devices, smart healthcare devices and attitudes to smart textiles. They concluded that there is a need for HCD specifically for E-textiles developed for healthy ageing.

Technology acceptance for older adults is affected by cost, privacy concerns, perceived need, ease of use and whether it is obtrusive [8,9]. A study conducted on the attitudes of older adults versus young adults' adoption of activity trackers showed that older adults are slower to adopt the technology. The ease of learning was the greatest factor affecting the adoption of the technology [10]. A systematic review of technology acceptance surrounding wearable exercise trackers for older adults had two interesting findings. The first is the small sample sizes, which have the potential for bias and there is a lack of information on the needs and wants of the older adults [11]. Therefore, asking women about their clothing preferences as well as their views on falls and attitudes to technology was prioritised.

When designing any monitoring systems for the older population the MATUROLIFE project, a large EU Horizon 2020 project running from 2018-2021 is often referenced [12,13]. The MATUROLIFE project was very large, involving nine countries (France, Italy, Spain, Belgium, Germany, Poland, Slovenia, Turkey and the United Kingdom). The MATUROLIFE project's methodological approach was based on co-design. They conducted semi-structured interviews to gain insight into the daily lives of older adults. These were followed by co-design workshops allowing the participants, designers and researchers to work together to create the final prototypes. There were two types of workshops, one for exploration and one for the design of the product itself. The exploration workshops were used to continue to gain insight into the priorities of the older adults and resulted in the three types of products to develop. The product workshop was used to inform the design of the products using the needs and desires given by the older adults along with the designers and the researchers.

4.2 Methods

4.2.1 Interview

The initial stage of the study involved recruiting participants 65 and over to conduct semi-structured interviews. The participants were recruited using the snowball sampling method [14]. This method of sampling is often used for qualitative research. It involves the researchers initially reaching out to a small number of contacts. These contacts then recommend others that are willing to participate, resulting in twelve female participants. Each participant was given an information sheet about the study and signed a consent form. The age ranges of the women are shown in **Error! Reference source not found.**. Ethical approval was granted by the Nottingham Trent University College of Art, Architecture, Design and Humanities Research Ethics Committee in December 2021.

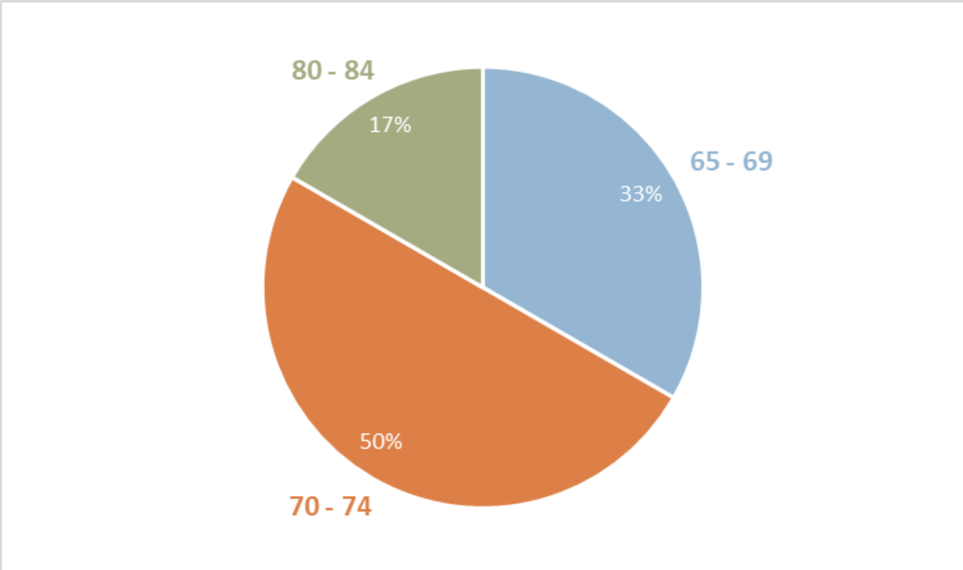

Figure 4.1 Chart showing the age of the female participants

The interview explored four key topics; clothing preferences; current and future health needs; attitude towards technology including wearable, health and monitoring devices and fall, fall prevention and fall detection. These topics and the questions were formulated by the authors and shared with other colleagues to refine them. There were 28 questions in the interview schedule and the interviews lasted approximately 30 – 45 minutes. The interview schedule is presented in the appendix. The interviews took place on Microsoft Teams (Microsoft Corporation, Washington, USA), and the audio and video were recorded, as well as the transcript. The transcript was reviewed using the audio. Once an accurate transcript had been developed the video and audio of the interviews were securely deleted. Each participant will be referred to using the code F for female and a number. The interview data was analysed using thematic analysis and coding was done in NVivo (v.12 Pro for Windows, ©QSR International, Burlington, Massachusetts, USA). Thematic analysis is a qualitative analysis method that is used to identify patterns (or themes within the data) [15]. The interview data also contained information that has been analysed more quantitatively when the questions asked provoked a yes or no answer. The authors are aware that the information from these interviews is not statistically representative due to the small sample size.

4.2.2 Prototype Development

To develop a range of E-textile prototypes, the study utilised research on the ideal position of the sensor for near-fall detection [16,17], which is presented in Chapter 3: the waist, thigh or ankle, and combined this with the interview data from this HCD study. The four-person prototype development team was interdisciplinary with expertise in E-textile development, E-textile design, textile and fashion design, seamless knit manufacturing, and pattern cutting.

Both the ankle and shorts prototype were seamlessly knitted with an integrated channel for yarn sensor insertion and a pocket to accommodate the supporting hardware using a Stoll CMS ADF 32W E7.2 (Lengede, Germany). The ankle prototype has a rib on the bottom and top for knit stability and to stop curling. The body of the ankle prototype is a knitted single jersey structure. The ankle prototype was made of three yarns including Stretchline black Lycra 16/SCY/090 and 20/DCY/003 as well as Nylon 6 70/68/2 in black. The shorts prototype has a rib on the bottom legs and at the waist for knit stability and to stop curling. The main structure is a knitted single jersey structure. The yarns used in the shorts prototype included Nylon 6/6 2/78/68 in white, Zimmermann Ultralastic 5879XX-0301 and Stretchline white Lycra 16/SCY/090. The patch prototype was made using cut-and-sew techniques to an original pattern template developed by the team.

For the prototypes, the hardware was simulated using laser cutting 3mm thick sheet acrylic to the size of the envisaged components: an Adafruit Trinket 3V P1500 (27mm x 15.5mm), a 3.7V 40mAh Lithium Polymer Battery (15mm x 15mm), a Pro Trinket Li-Poly backpack power management unit (17mm x 15.7mm) and a data management unit (21mm x 15.7mm). At this stage, this combination of components had not been tested and was being used to simulate the potential bulk and handle of a possible configuration.

4.2.3 Focus Group

A small focus group was held to inform the participants about E-textiles to raise awareness, so that they could give better and fuller answers to their experience. Five women attended the focus group held at Nottingham Trent University in May 2022, with the average number of participants for a focus group being six to eight [18]. These included four participants from the interviews and an additional woman was recruited subsequently also using the snowball method. It was important that the focus group was held in person to allow the participants to handle the prototypes.

During the focus group, each prototype was discussed individually. This was followed by a discussion around aesthetics to help them envisage what styles the prototypes could have. The audio of the focus group was recorded, and each of the three facilitators made notes during and directly after the session. The recording was transcribed, and thematic analysis was performed on the data, as for the interview data.

To ensure all participant's opinions were captured a questionnaire was given at the end. The questionnaire asked the participants to numerically rate the three prototypes according to comfort, sustainability, practicality, ease of use, durability, appearance, materials, features, feel and overall design from 1 – 5, with 5 being the most positive. They were also given space to justify these choices. In addition, they were asked to rank the prototypes from 1-3, with 3 being the most favourite and 1 being the least. The contents of the questionnaire are presented in the appendix.

4.3 Results

4.3.1 Interview Data

4.3.1.1 Clothing Preferences

Three important themes were found when exploring people's attitudes towards clothing: physical comfort, emotional comfort and quality. Emotional comfort and physical comfort are intimately linked and were often mentioned within the same sentence.

4.3.1.2 Comfort

The word comfortable was used multiple times by several participants as a clothing priority. Comfort was not only concerning physical comfort but also emotional comfort. In this sense, emotional comfort means wearing something that is flattering, stylish, age-appropriate and appropriate for the context in which it is to be worn. F2 was direct in connecting tightness with comfort, possibly both emotional and physical, by saying, "*I don't tend to go for anything too tightly fitting, again, cause of comfort.*" Although each participant expressed a range of individual clothing preferences, when asked about the preferred fit of clothing, tight-fitted clothing was not wanted, especially around the waist; for some, this was primarily linked to health issues and physical comfort, as indicated by F3.

> *"I've really gone off tight-fitting clothing. […] I quite like having narrower trousers. With a long top over the top, but again, anything that really cuts into my waist, it just sets off digestive problems, basically."*

For others, it was emotional comfort and wanting to hide perceived undesirable parts of themselves as indicated by F1, *"I don't want to wear things that are so tight that they show every little bulge".* The stomach was seen by the interviewees as a particularly disagreeable body part to show off, with F7 saying *"I try and buy a little bit of loose fitting so that... It's not visible, like my stomach is not visible."* as well as F9 saying *"I don't like tight things across my tummy… at all. I can't bear tight clothing in that area."*

In addition to not wanting tight-fitting clothes and being comfortable, it was clear that people still want to look their best. F3 *"I want things to be comfortable. I want them to look good and be flattering as far as possible."* When referring to a specific item of clothing F12 said *"I quite like it just feels nice and comfortable and it feels like it costs money as well … the finish and the way it hangs and the way it fits is really nice."*

4.3.1.3 Age-appropriate clothing

Part of wearing something that is flattering is that it feels like it suits you as an individual. This includes feeling like it fits your style preference and matches the age you wish to show. Even though the participants were older adults, there was a clear distinction between them. F9 said

> *"I don't like to choose something to wear that I think it makes me look as if I want to be wearing something too young for me […]. I want to wear something that is suitable but trendy and comfortable…. I like to seem to be sensible for my age. But not looking old fashioned and dreary."*

For this generation, it appears that finding age-appropriate clothing is an issue with F1 saying,

> *"I think actually for our age group finding nice clothes that don't make you look like mutton dressed as lamb and yet don't make you look ancient is quite an issue."*

This feeling was shared by F5 as she discussed how difficult it is to find shops catering for her age range. *"I find there's not many shops that really cater for 65-year-olds or 66-year-olds, so we're sort of in-between".* She goes on to say *"When my parent my mum was this age, she had all gone to a much older tired style clothing. Whereas these days most of us don't."* This shows a desire to continue to look young yet age-appropriate. These wants are not individual and this is also expressed by F12.

> *"I think at the moment because I still shop in, I would say sort of middle-age rather than older-age fashion retail outlets. So things you know, things like jumpers. I went into COS for looking at cardigans and jumpers the other day in [*] and you know, they're all cropped, and cropped jumpers look really good on younger women, but you know, not at my age. They look awful."*

This area of difficulty expressed by the women in this study was shared with the group of women who took part in the Emotional Fit project [5].

4.3.1.4 DIFFICULTIES WITH CLOTHING

Lastly when asked about clothing difficulties a third of the women experienced issues affecting their hands. Women are more likely than men to develop arthritis as they age [19]. **Error! Reference source not found.** shows a chart displaying the main difficulties of the participants when getting dressed, as extracted from the interviews. These clothing difficulties affect the types of clothing that people are willing to buy. F8 had reduced dexterity from an old injury making the use of zips and buttons hard. She said, *"the difficulties I have sometimes are doing up zips […] and also I mean sometimes buttons".* F3 said *"Coats and cardigans is something I need it to be quite stretchy and putting coats on I need to be quite careful cause it can hurt."* F4 talked about having arthritis and said,

> *"I've got jeans with the zipper, I struggle with it and because I've got arthritis […] and the jumpers I wear not only trousers, even the jumpers, if they are bit stretchable, you know, then it's easier to put on and take it off".*

Looking at these quotes, stretch clothing is worn for ease and stretch denim was a preferred material for jeans. Nine of the participants stated they wore some form of stretch garment, either stretch jeans, a jumper, leggings for yoga, or thermal layers.

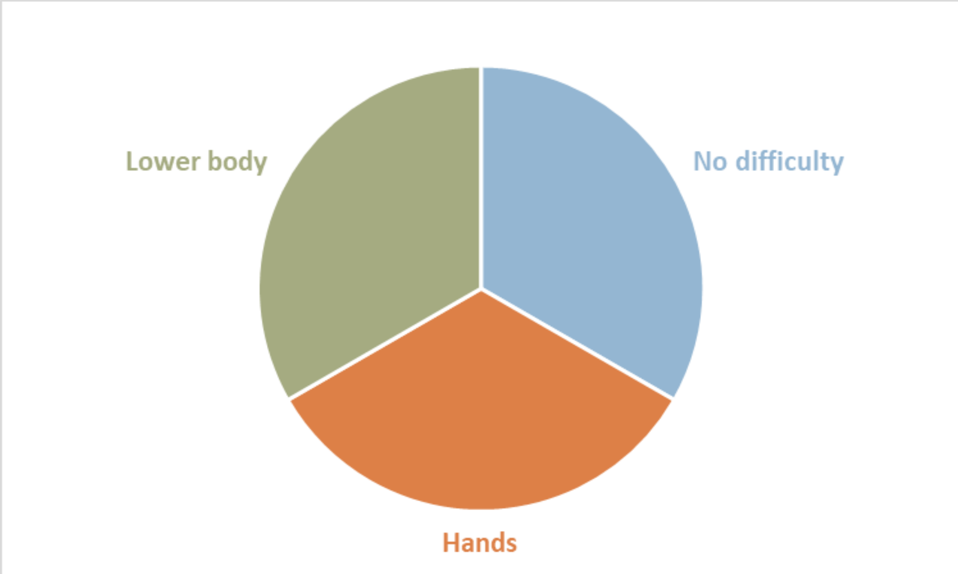

Figure 4.2 Chart showing the clothing difficulties of the participants

4.3.1.5 Materials

During the interviews, the choice of materials for clothing was not mentioned very often as it was not a specific topic for questioning. However, it was mentioned when clothing preferences were discussed. There was a preference for natural fibres such as cotton and wool with the addition of a synthetic stretch material. F3 stated, "*I really do like natural fabrics as well, cottons and things with a bit of stretch*". F4 had a similar sentiment: *"mostly it's polyester with cotton, something stretchable."* Whenever wool was mentioned, it was to keep warm; F9 said that in the winter she looked for clothing with some percentage of wool.

Natural fibres are seen to be more environmentally friendly and sustainable. F8, when talking about her favourite item of clothing, said, *"It's made of cotton. So, it's, you know, it's a sustainable fabric."* When describing her favourite garment, F5 discussed finding wool itchy and therefore choosing synthetic fleece as the alternative. However, she also mentioned known issues with synthetic fleece being the release of microplastics into the environment. The idea that so-called natural fibres like wool and cotton are inherently more sustainable is overly simplistic. Synthetic fibres can make clothing more durable and natural fibres can use large amounts of water to grow and process. Independent of the material from which a garment is made, a key approach to reducing its environmental impact is to extend its lifespan. A strategy that has also been highlighted for E-textiles [20].

4.3.1.6 WASHING OF CLOTHING

Another important aspect of designing an E-textile was finding out about washing habits. This is because washing the technology will require extra care. If participants would prefer not to take the extra care, this needs to be accounted for in the design. When discussing priorities for clothes this question was answered. It was clear that using the washing machine is the preferred method. F6 said she would *"…never buy anything that says hand-wash, everything needs to go in the washing machine."* In a similar vein, both F9 and F10 avoid clothes that ask for dry-clean only. Essentially, the clothes that can be washed in the machine are easier to care for. The interviewees were not asked how they dry their clothes, which would also be a consideration for the design of any E-textile that is meant to be washed.

4.3.1.7 TECHNOLOGY

Attitudes towards technology were explored to gauge how comfortable people are using technology and integrating it into their daily lives. As these interviews were performed online there is a bit of bias within these answers, as all participants were willing to use technology and had the technical competence to participate in a teleconference. Even so, there was a varied response to technology, ranging from fear to acceptance. For the most part, people liked technology, but they find it hard to use and need help from another person. F12 clearly communicated her anxiety about technology saying, "*I'm afraid of it"*. Two people had similar opinions on the usefulness of technology but with different attitudes to technology itself. F7 was more positive; *"Technology is good, but I'm not very good with technology"*, yet F3 said, *"I just view it as a necessity, but I don't take any pleasure in it"*. Another interesting attitude was similarly mixed, with F2 saying *"I'm for it as long as it's beneficial. I do not wish to be looking at my watch all day to be seeing how many steps I've done".*

Only three participants owned wearable technology in the form of a smart watch. Several participants acknowledged that owning wearable technology can induce obsessive behaviour. F1 stated, *"We had a Fitbit which I was actually a bit obsessed with really. You know, I've got to do so many steps every day"* and had eventually stopped using it. F2, did not own smartwatch but talked about the effect of a Fitbit on her husband *"I think you then become a slave to it*". By contrast, six of the twelve participants own some form of health-monitoring device. The COVID-19 pandemic caused two participants to invest in these types of devices. F5 clearly stated "because of COVID, we've got an oxygen meter".

When asked where they would be willing to wear technology, the overwhelming majority said the wrist and liked the idea of a watch or jewellery. In addition, the neck came up in the form of a necklace; however, when asked where they are not willing to wear technology, the neck was also mentioned. The responses for where they would not be willing to wear technology was much more varied. However, there was a touch of resignation to wearing a device if it was compulsory for health needs. F1 said,

> *"If it was something that was very important from a health point of view, then you would just have to accept it and wear it where you had to wear it wouldn't you. Don't think I would be over fussy about that, if it was for a medical reason."*

4.3.1.8 Falls

When discussing falls most participants did not have mobility, stability or movement issues and this is shown in Figure 4.3a. However, that does not mean that the prospect of a fall was not a concern, as shown in Figure 4.3b. Falls are a concern, because there is an understanding that once you reach a certain age and have a fall the effects can be devastating. Some of the participants talked about older people they know, they care for or have cared for, which is why they worry about falls, but they don't see themselves as that old themselves. F1 said

> *"I can think of several instances of elderly people, and when I say elderly a lot older than me elderly, who've had falls, in some cases, become a fatality in the end because it's been such a shock to their system".*

When discussing wearing the near-fall detection E-textiles F2 said *"elderly, very elderly people, I think it might be helpful".*

There does appear to be a distinction between being an older adult and being elderly, which is clear in the quotes above. When asked about wearing an alarm to call for assistance following a fall, F2 said, "*not now but if I was much older than I am, yes, definitely*". This sentiment was shared by other participants, for example F4 talked about falls becoming more of concern as you age *"Yeah, it's, as you grow older this is something you hear".* F9 talked about how as people age, they tend to ignore problems, *"Old people become really proud, and they don't, you know, realise that they're not as good as they used to be with their movements and so on",* but as she is 82, statically a fall is incredibly dangerous for her as well. F6 was also concerned about falls and differentiated between a younger person falling compared with an older person.

“The biggest concern about being older is that if you're younger and you fall, people say you've fallen over. If you're older and you fall, people say, oh, she's had a fall, as if it's an entirely different thing.”

Yet F6 would not be willing to wear a device that calls for assistance as she said, *“I think I’d cross a line”*. The idea of being seen as or accepting oneself as an older person is not at all appealing.

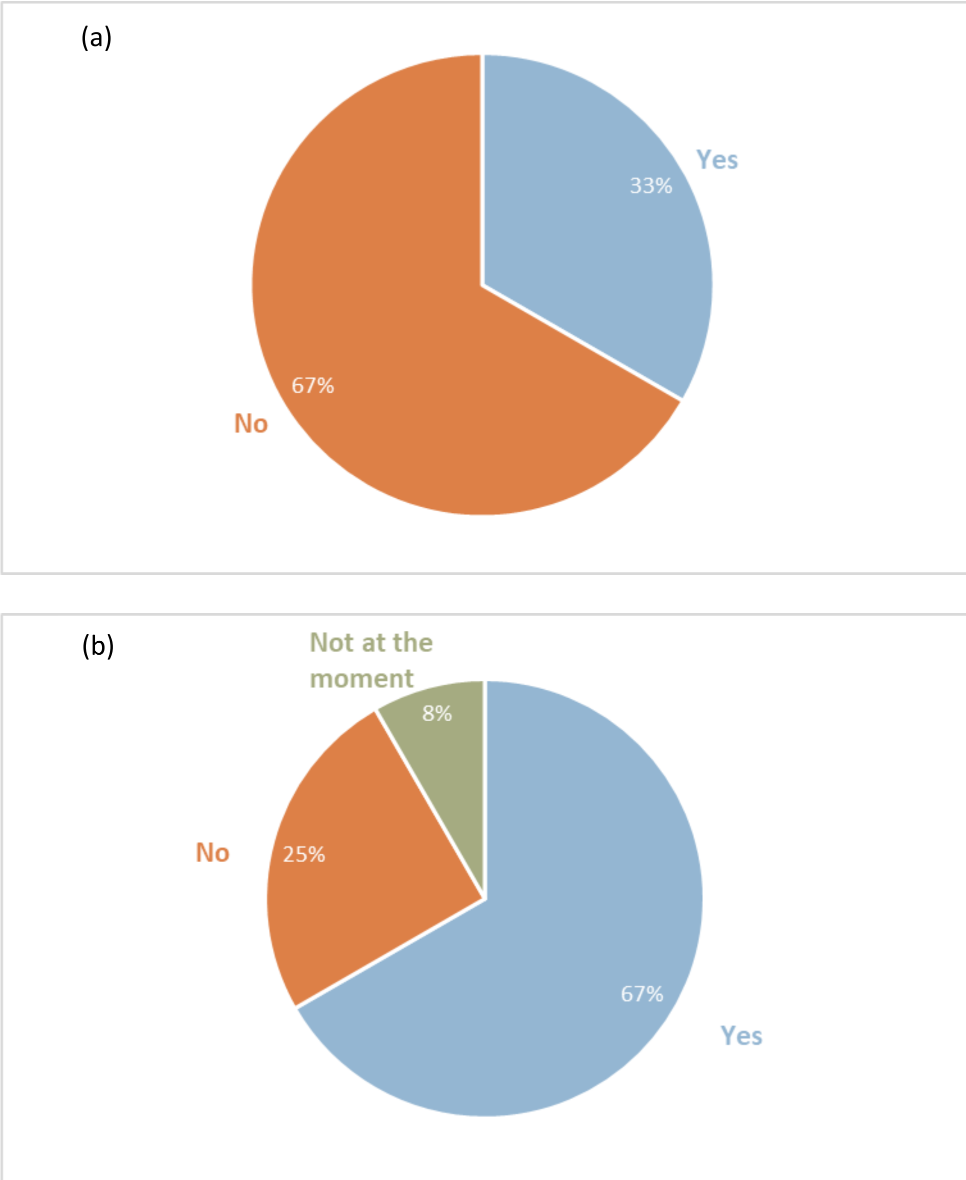

Figure 4.3 (a) Pie chart showing who currently has mobility issues and (b) pie chart showing how concerned participants are about falls

Figure 4.4 shows a pie chart visually displaying the number of participants willing to wear a preventative device. When asked if they are willing to wear a device for fall prevention, over half said yes, but not at the moment was also a common answer. An example of this is a quote from F7: *"Well, at the moment I don't need assistance, so I wouldn't".*

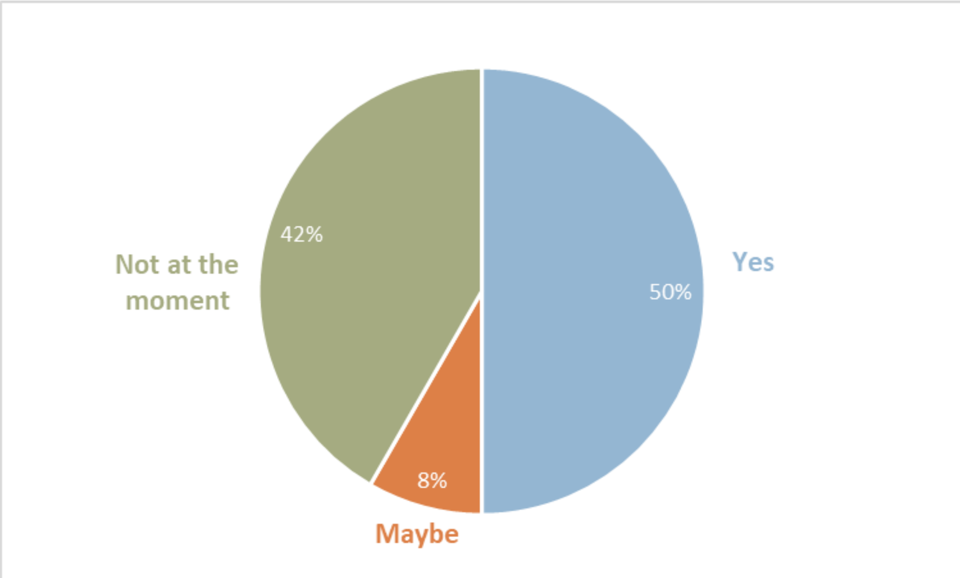

Figure 4.4 Chart showing the willingness to wear a fall prevention device

4.3.1.9 E-TEXTILE WEARABLE DESIGN

Interviewees were asked how they felt about wearable technology being visible or concealed (Figure 4.5a) and whether they would prefer wearable technology to be part of a garment or attachable to an item of clothing (Figure 4.5b). None of the participants actively wanted anything visible unless it was something to show off, like a Fitbit or jewellery. Additionally, most people wanted it to be attachable, for reasons that included not interfering with what they want to wear, the cost of buying multiple E-textile items, and for washability. F6 said *"From a practical point of view, it's probably something that you attach, so you could put it on different garments."* F10 said *"I think attachable because you need to wash the garment, don't you?"*. F1 discussed wanting the most cost-effective solution, saying *"Some of it would be on price. If it's cheaper to have something that then attaches to a garment you've already got rather than buy a specific garment, then I think that would be my first choice".* F2 talked about her perception of the benefits of an attachable item both in terms of washability and flexibility stating,

> *"I think probably attachable to an item of clothing because that garment would have to be washed. If you had some, something that could be*

attachable. You could attach it to whatever you're wearing or adapt your clothing to suit, but if it's actually in a particular garment, you're very limited."

However, in the minority, F4 thought integrated would be less visible so preferred that *"because it perhaps would match whatever I'm wearing or, you know, it won't show that much."*

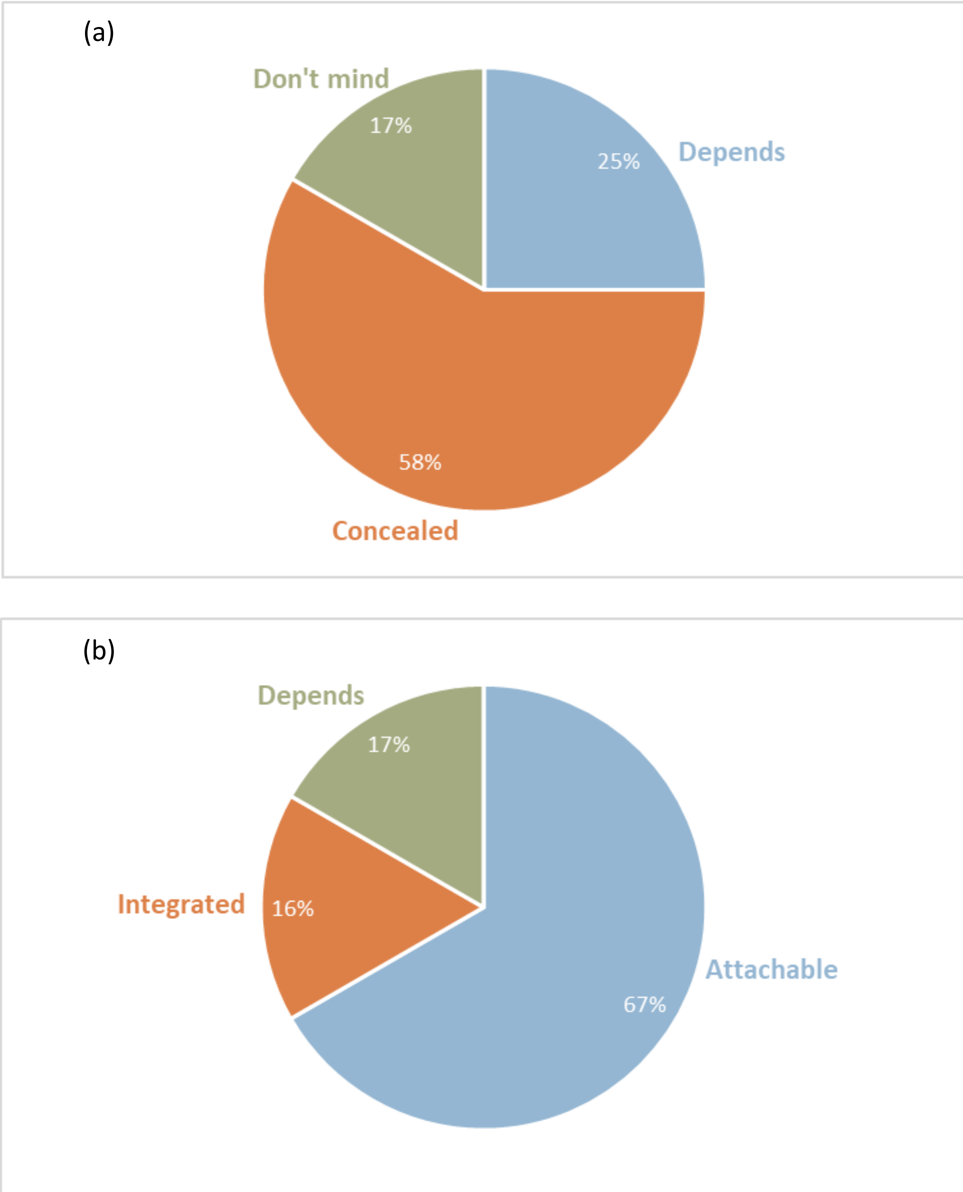

Figure 4.5(a) Pie chart showing whether the participants would prefer the electronics to be concealed or visible and (b) which integration technique is preferred

It seemed that many of the interviewees were envisioning something like a smartwatch or smartphone attached to their body. This clearly influenced their responses, particularly when discussing specific locations on the body (ankle, thigh or waist) for near-fall detection. Of the three given locations, the thigh was a not popular. The waist was the most popular choice. When discussing the ankle, it seemed people were imagining an ankle tag like those worn by individuals under house arrest.

4.3.2 Prototype Development

The information collected from the interviews was analysed and used to develop the three prototypes: an ankle prototype (Figure 4.6), shorts (Figure 4.7) and a patch (Figure 4.8), one for each of the three positions found to be suitable for near-fall detection using the sensor, presented in Chapter 3 [16,17]. The construction of the three prototypes is discussed in Section 4.2.2. These were non-functional prototypes using laser cut plastic parts to simulate the feel of the real electronics. The idea was that the hardware module to control and power the E-yarn and communicate externally could be detached from the E-yarn for washing purposes. It was also envisioned that the hardware could be modular so parts could be replaced for repair or to upgrade the product as recommended by Hardy *et al*. [20] and Köhler [21].

Important aspects of the prototypes' design were that the proposals should be physically comfortable, concealable, which fits with the requirement for emotional comfort, and possibly attachable rather than integrated into a full garment. As stretch clothing was mentioned by several participants, this was incorporated into the designs. To accommodate the desire for something that could be concealed and attached, and that wouldn't limit an individual's daily garment choices, the prototypes developed were accessories, under garments or a patch that could be attached to a garment.

Only four of the participants had a clear idea of what E-textiles are and responses indicated that when they were asked about wearable technology, they were imaging a bulky electronic item. Therefore, the design team integrated electronics into two of the prototypes, but with the supporting hardware detachable for washing to test whether when faced with actual examples the participants opinions would change.

Bearing in mind that quality and value for money were of interest to the participants, and the design team's aim to make a long-lasting product, the ankle prototype was created to eliminate the parts of a sock that tend to wear through first, namely the heels and toe. It also potentially limits the needs for washing as it can be worn over socks. The design was also a response to a participant's suggestion. F3 talked about their grandson not being able to keep his sock on and mentioned, *“these things called sock-ons which you put over the sock…. it's the sort of thing that I think I'd be able to cope with as well. I just thought what a good idea they are, but then, then you could just wear your normal socks and have that over the over the top, and then they could be made quite discreet and I think they're quite comfortable.”*

Figure 4.6 Seamlessly knitted ankle prototype

The E-yarn sensor was positioned in a channel that ended below the ankle bone while the rest of the electronics were in a module at the back to the ankle intended not to inhibit movement and to be out of the way of shoes.

The shorts were inspired by anti-chafe shorts that are commercially available from multiple retailers. They are used to prevent thighs rubbing together, under trousers for extra warmth and under dresses or skirts as an alternative to a slip. In this design, the main electronics module was positioned on the waist and the sensor was on the upper thigh/hip.

Figure 4.7 Seamlessly knitted shorts prototype

The third prototype (patch) was designed to incorporate all the electronics as a fully attachable/detachable textile piece. For the focus group the patch was attached to commercially available underwear using a type of popper.

Figure 4.8 Cut and sew patch attached to commercial underwear sample

4.3.3 Focus Group Data

4.3.3.1 Ankle Prototype

The views of the participants on the ankle prototype were varied. On first appearance F6 clearly stated, *"I wouldn't wear it."* However, as the conversation continued, she said that she *"might wear it in the winter".* As the focus group was held during hot weather, this seemed to influence people's responses as their concern linked to emotional comfort and they did not want to be seen wearing something on their ankle if their legs were exposed. The participants also stated that the ankle prototype would be the most comfortable of the three designs at night. However, the majority thought that a fall prevention device would be most needed in the daytime, with F12 saying, *"the risks are greater during the day"*. This is not necessarily the case, as falls tend to occur at night in the bathroom [22]. There was a general agreement that owning multiple socks would be useful, as it would allow for different colours, and washing. In addition, multiple socks with the sensor embedded only require one hardware module as it can be attached to other socks.

Unlike most of the participants, F12 would be willing to wear the ankle prototype now if it was commercialised, which links to findings in technology acceptance studies that perceived need is critical to acceptance [8]. Health issues, where having a fall could be particularly detrimental, made her more receptive to wearing a fall detection device. She also gave some design suggestions, such as a longer sock so the hardware can sit above a boot. When the participants were touching the device and taking the hardware module out of the pocket, it was mentioned by F13 that getting the hardware module in and out was *"a fiddle".* This could be easily improved in future iterations of the design.

4.3.3.2 Shorts Prototype

Similar to the ankle prototype, the shorts prototype solicited mixed reactions. Part of the problem was that it was hard for some of the participants to see past any design flaws in the protype in front of them, rather than them seeing them as a first iteration. Even so, there were positive attitudes towards the shorts. Comments by F3 included, *"I do wear short leggings under dresses, and I find it really comfortable"* and *"to me it's like wearing sort of a slip but it works properly".*

In addition, there was conversation about changing the design to suit them, such as the waist which was described as being for *"a young person's waist"* by F12. They talked about having the waist higher or lower, as well as less thick or tight. The waist height was selected by the design team based on wear testing. The team were aged under 40 so the participants' assessment indicates that it would have been beneficial to undertake a co-design process to include the perspective of women over 65 throughout the design process for the prototypes. The authors are aware that in the current colour, when not worn, they look like and were described by the participants as bloomers (a 19th century women's garment style for the lower body, used here in a derogatory manner to indicate something old-fashion and unstylish). F3 stated, *"I'd definitely consider wearing things like the shorts if they were more comfortable and more trendy and not like granny bloomers."* In addition, to keep within the theme of looking trendy, F3 also reflected that the shorts could be altered: *"You could turn those into leggings really easily and be very trendy".* The shorts are a seamless design and could be adapted in multiple ways to meet the participants' requests.

4.3.3.3 PATCH PROTOTYPE

Whilst discussing altering the design of the shorts prototype, there was a conversation about underwear. This was because the shorts were also seen potentially as underwear. The group discussed putting the electronics into a pocket in underwear. This led nicely onto talking about the patch prototype. Although it was explained that the patch could only be placed at specific points on the body for accurate detection, the device was seen as attachable anywhere and therefore the participants were more enthused about this prototype. One participant wanted to put it inside her bra, which would not give accurate data. F6 said, *"I'd want that on my outer clothes. I'd want it on my trousers or my skirt or something I wouldn't want it on under because you want to put other clothes on. I'd want that to be the last thing I was wearing."* If it was attached to a waistband, positioning the patch on an outer garment could be entirely compatible with accurate data collection. The only apparent disadvantage to the patch expressed by the participants was the poppers used to attach it to fabric. The participants struggled with the poppers and F4 said it was *"a bit fiddly".* This is an aspect of the design that could be improved.

The patch could be designed so that a wearer could use it at the various viable locations if it was able to be calibrated, but gaining consistent data would be more challenging. What the preference for the patch prototype shows is the extent to which the group valued having control over their garment choices whether for reasons of aesthetics or comfort. Because the device was seen as optional and an indicator of ageing rather than a health necessity, the bar for acceptability for many would be very high.

4.3.3.4 AESTHETICS AND MATERIALS

To help the participants conceptualise what the final garment could look like, they were presented with several moodboards indicating various colour and material combinations. The preferred aesthetic was sportswear; however, there was some discussion around classic colours, i.e. black, white and nude.

During the focus group, different materials were discussed and, like in the interviews, there was a preference for natural materials, as manmade materials were thought to make you uncomfortably warm. However, F3 talked about owning some anti-chafe shorts from M&S, which are made of synthetic fibres, but were described as *"not hot"* when worn over normal underwear. Noting the preference for sportswear, which tends to be synthetic, it was clear that the design was more important than the material. There was a short discussion on whether synthetic materials are more sustainable than cotton, between F3, F12 and Facilitator 1.

> *"Because some of the synthetics are really comfortable to wear."* – F3
>
> *"Tencel and things like that. I don't know how sustainable they are. It's difficult."* – F12
>
> *"So it's primarily Nylon, it's got cotton in the gusset, but it is mainly Nylon."* – Facilitator 1
>
> *"But then you know if something like that is well made and lasts for a long time it's probably more sustainable than cotton ones which actually do shrink and"* – F3
>
> *"Go into holes and you have to get rid of them."* – F12

As consumers, it is difficult to know what to choose as a sustainable option and there is much discourse within academia as well. The discussion around materials and sustainability was mostly limited to F3 and F12. F13 added that she finds synthetic materials hot and F6 showed a preference for light materials. She stated, "The new sportswear is made in breathable materials, isn't it?"

4.3.3.5 QUESTIONNAIRE

The results of the questionnaire, held at the end of the focus group, supported the opinions expressed during earlier discussions. Table 4.1 shows the in-depth ranking that was given to each prototype and by this data the patch was the preferred option, followed by the ankle prototype and the least favourite was the shorts.

Table 4.1 Rankings of each prototype

	Ankle prototype					Shorts prototype					Patch prototype				
	A	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**
Comfort	3.5	5	4	3	3	2	4	4	3	3	3	5	5	3	5
Ease of use	3	2	5	5	4	3	4	4	5	3	4	4	4	4	4
Practicality	4	3	4	3	3	3	4	5	3	3	4	2	5	4	5
Durability	3	5	3	5	5	3	5	5	5	4	3	4	5	4	5
Sustainability	3	5	5	5	5	3	4	4	5	4	3	4	3	4	5
Appearance	3	5	4	1	2	3	2	4	1	3	4	5	5	3	5
Materials	3	4	5	5	3	3	2	4	2	3	2	5	5	4	5
Features	3	3	4	3	3	4	4	4	5	3	4	5	5	3	5
Feel	4	5	5	5	4	3	4	4	3	3	3	5	4	3	5
Overall design	3	5		1	4	3	4		2	4	3	5		3	5
Total	**32.5**	**42**	**39**	**36**	**36**	**30**	**37**	**38**	**34**	**33**	**33**	**44**	**41**	**35**	**49**
Overall Score	**185.5**					**172**					**202**				

However, when asked to rate the prototypes in order of preference (shown in Table 4.2) while the patch remained the most popular option the least favourite became the ankle prototype. This indicates that the difference in preference between the ankle prototype and shorts was minimal.

Table 4.2 Rating of each prototype

Rating	A	B	C	D	E	Total
Ankle	1	2	3	1	2	**9**
Shorts	3	1	3	2	1	**10**
Patch	2	3	2	3	3	**13**

The reason for conducting the focus group was not to obtain a definitive result. With only five participants having taken part in the focus group the marginal differences in preference between the three prototypes needs to be treated with caution. The sample size is not of statistical significance and a larger group may have produced a different result. Much as the data from the interviews and previous studies of the clothing preferences of older women or people in general shows, there were always likely to be diverse opinions. This diversity reflects the participants' different body shapes, ailments, insecurities and identities, the image an individual wishes to cultivate and project. Importantly none of the prototypes were wholly discounted and participants envisaged using different ones according to the circumstance, i.e. the ankle prototype at night and the shorts when wearing a dress. This outcome means further research would be required if the aim was to commercially produce one item and that for technical testing all three are viable options.

4.4 DISCUSSION

Despite several interviewees being in their 70s and above, most did not perceive themselves to need the technology yet, a factor which is known to be key to technology acceptance [23]. Within the focus group, this was explored further. The suggestion was that the technology should be recommended by medical practitioners, either nurses at a yearly check-up, physiotherapist, or chiropractors. It was clear during the interviews and within the focus group, that although they know they are older adults, they do not see themselves as elderly. This highlights the importance of design, as many were unwilling to wear anything they perceived as stigmatising or unattractive. To accommodate this, the prototypes were designed primarily as accessories, as participants did not want technology to dictate their outfit choices. Other preferences were the ability to wash clothing in a washing machine easily and the use of natural fibres along with stretch. The discussion around materials was limited in both the interviews and the focus group, making it difficult to draw a definitive conclusion.

Contrary to the perception that seamless integration should be the priority when designing E-textiles, participants were concerned that integrated technology would limit their clothing choices and oblige them to own multiple identical items. This is an important outcome that must be considered when developing E-textiles for older adults in the future. Comfort was the participants' most frequently cited priority when choosing clothes, and there was an inclination towards looser fitting garments. The three prototypes: an ankle prototype (Figure 4.6), shorts (Figure 4.7) and a patch (Figure 4.8), were designed to align with their preference for comfortable, easy-care clothing while allowing flexibility in clothing choice and to be invisible when worn. E-textile developers need to bear in mind both older people's physical needs and the role clothes play in self-expression and social signalling. This study and others

[4,5] have shown that these factors become increasingly complex for women as they age, with aliments dictating what is comfortable, the desire to hide their perceived imperfections and endeavouring to appear neither too old nor too young.

Falls are a concern for most of the women; however, there is reluctance to admit that they are at risk, unless they already have an underlying condition. During the focus group F13 said that

> *"a lot of people don't want to admit that they're at risk of falling or at risk of anything as you get older. I'm perfectly fine, I can carry on, there's nothing wrong with me."*

Along with *"you can kid yourself that, oh that was just a one off, can't you? Sometimes you just don't want to believe"*. This indicates that there is an understanding that as you age things can go wrong, yet it is easy to delude oneself into thinking that there is no problem. It highlights the benefit of near-fall monitoring in case multiple losses of balance are being ignored. There is a definite resistance to using this technology, as F12 said during the focus group, *"If I started to feel a bit wobbly, because you'd know, then I think I would but not unless you felt a need for it or something had happened and you needed to wear it."* This resistance makes the design of the object all the more critical. It highlights the need for human centred design and, in future, a co-design approach when developing E-textile wearables for the ageing population to make them as appealing as possible.

Although the patch came out as the preferred prototype, the participants expressed interest in owning several of the proposed objects so they could wear them according to how they felt, what they would be doing and how they were dressed. F3 said *"I think at the moment I could envisage having a different garment for different activities that I might be doing".* The shorts and the ankle prototype were also preferred by some, with the main deterrent to the ankle prototype being the bulky electronics. As not all participants were familiar with anti-chafe shorts, the shorts were seen as an extra layer or too long. Both the ankle prototypes and the shorts can easily be altered for different preferences. The disadvantaged to the current iteration of the prototypes was that the hardware module was fiddly for them, either to put it within the pocket or use the poppers, however this could be easily improved.

4.5 Conclusions

Falls are a concern for older people. However, whilst they are still mobile, the need for a fall prevention device is not wanted. It was difficult within the focus group to explain to the participants the need of this technology. The stigma of being old was too great to overcome. They would rather wait for a problem than to prevent the problem from occurring.

Comfort was the biggest priority for clothing, and otherwise people's tastes are very varied due to their individuality. Therefore, the prototypes were made as accessories to be worn under or over garments. The three prototypes made all had advantages and disadvantages. The biggest disadvantages being the current bulk of the electronics module which was in this first iteration fiddly attach and remove or detach. The patch was favoured over the ankle prototype and the shorts, however there was a misunderstanding of how the patch could be used. The ankle prototype came second when looking at the in-depth rankings of each prototype.

The ankle prototype design will be used to develop a functional prototype. This functional ankle prototype will then be tested in a trial involving young healthy volunteers as a proof of concept that an electronic textile fall and near-fall detection system can accurately classify fall and near-fall events.

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CHAPTER 5. DEVELOPMENT AND TESTING OF FINAL E-TEXTILE DESIGN

ACKNOWLEDGEMENTS

The work presented in this chapter is published in the journal MDPI Materials [1]. Parts of this chapter make use of the text from the article under CC BY 4.0 [2]. The author list of the article is **Zahra Rahemtulla,** Alexander Turner, Carlos Oliveira, Jake Kaner, Tilak Dias, and Theodore Hughes-Riley.

The experimental work was conceived and conducted by Zahra Rahemtulla with Dr Theodore Hughes-Riley providing input and supervising. The data collection, organisation, visual analysis, and data interpretation was conducted by Zahra Rahemtulla.

The machine learning model was created by Dr Alexander Turner and has been used in other work [3–5]. Dr Turner trained and tested the network for this study. As a result, he provided the description shown in Section 5.4.1.4.

Carlos Oliveira designed and produced the knitted over-sock.

Prof Jake Kaner and Prof Tilak Dias provided supervision.

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5.1 INTRODUCTION

This chapter presents the engineering of a suitable motion sensing electronic yarn (E-yarn), E-yarn testing, hardware development and the testing of the electronic textile garment (over-sock). The over-sock developed in Chapter 4 has been altered for this work so that the pocket for the hardware was vertical and directly above the E-yarn and the integration channel for the E-yarn is wider. This was to ease the removal of the hardware module from the pocket and the insertion of the E-yarn. The hardware used was as small as possible and is no longer housed within a textile patch to keep to the design considerations.

The over-sock was used in a human trial as a proof-of-concept that a motion sensing E-yarn can be integrated into a garment and, in combination with a deep learning algorithm, detect falls. Each motion sensing E-yarn contained one commercially available inertial measurement unit (IMU) that measured acceleration in three axes and angular velocity in three dimensions. For the trial 13 healthy women were recruited. Each participant performed three types of activities of daily living (ADLs), a near-fall (stumble), and three types of falls, whilst wearing an over-sock on each foot. The collected data from each foot was visually analysed and a machine learning algorithm was used to classify the data.

5.2 E-YARN DEVELOPMENT

5.2.1 SENSOR SELECTION

At the beginning of the PhD project various inertial sensors were selected as possible candidates to create E-yarns based on information taken from the literature (Chapter 2), on their size, and what was commercially available in small-to-medium quantities at the time. Components larger than 4mm x 4mm x 2mm were not considered as they would create a very thick E-yarn. The pitch size was also considered to ensure that the sensor could be soldered. The table below shows what sensors were purchased for E-yarn development.

Table 5.1 List of sensors originally chosen for E-yarn development.

Sensor Type	Sensor Model	Sensor Size (mm)	Pitch size (mm)
Accelerometer	ADXL345	3 x 5 x 1	0.8 x 0.5
Accelerometer	ADXL337	3 x 3 x 1.45	0.4 x 0.25
Accelerometer	ADXL335	4 x 4 x 1.45	0.5 x 0.35
IMU	LSM303AGRTR	2 x 2 x 1	0.25 x 0.275
IMU	LSM6DS3TR	2.5 x 3 x 0.83	0.35 x 0.55
IMU	LSM6DSMTR	2.5 x 3 x 0.83	0.25 x 0.475
IMU	ICM 20689	4 x 4 x 0.9	0.25 x 0.4
IMU	BMI160	3 x 2.5 x 0.8	0.475 x 0.25

Initially, only two of each sensor was purchased. The three different accelerometers were bought as the ADXL337 had previously been used by the author to create a vibration sensing E-yarn [6], and the ADXL345 [7] and ADXL335 [8,9] have been used in other fall detection studies. The IMUs were chosen as they were in stock and were in the correct size range for E-yarn development. The BMI160 was the preferred choice as it was used in the MetaTracker used for the pilot study described in Chapter 3, and Bosch sold a developmental kit alongside the BMI160. Further the BMI160 had a desirable form factor for E-yarn development (3mm x 2.5mm x 0.8mm). The Bosch developmental kit was used for validation measurements in the pilot study described in Chapter 3. The pilot study concluded that it appeared to be beneficial to have both the acceleration data and the angular velocity data for classification of different activities. Therefore, an IMU was selected to create a motion sensing E-yarn.

Unfortunately, as a result of the Covid-19 pandemic, there has been a continuing global semiconductor shortage [10–12]. Accelerometers and IMUs are semiconductor sensing devices, therefore, this shortage has heavily impacted the availability of the inertial sensors. This shortage has meant that the BMI160 was no longer being manufactured later in this study and the replacement IMU (BMI270) had over a 52-week lead time. Additionally, all the inertial sensors in Table 5.1 were no longer available for purchase either due to long lead times or being discontinued later in this work. As soldering the sensors was difficult, there was a need for more than the initial two sensors purchased.

This led to the selection of the MPU-6050 (IvenSense TDK, California, USA), as it had been used in other fall detection studies [13,14] and had supporting software available, which was useful for the pilot study. Furthermore, this IMU was chosen as it is relatively small (4mm x 4mm x 0.9mm) with a pitch size (0.25mm x 0.35mm) that can be soldered manually. At the time of development, the MPU-6050 appeared to be the smallest IMU that could conceivably be soldered, was still available and in stock. Currently, MPU-6050 is no longer in stock from the original supplier and the author has used the amount purchased to develop the E-yarns. Only three E-yarns were successfully manufactured, from a supply of 20. Sensors purchased from alternate online suppliers, such as eBay and AliExpress, did not work.

5.2.2 E-yarn Manufacturing

E-yarns are manufactured using a three-step process. The first step of this process is to solder wires onto the desired sensor. In the case of the vibration sensing E-yarn, which contain the ADXL337, the soldering process was performed using an infrared spot reflow soldering system, PDR IR-R3 Rework System (PDR) machine as described in the paper [6].

This method used one Litz (BXL2001, OSCO Ltd. Milton Keynes, UK) wire and one multistrand copper wire. During the development of the vibration sensing E-yarn it was very difficult to solder the ADXL337 using the Litz wire under the PDR. Therefore, it was already known that it would not be possible to solder any other sensor requiring more than two terminals using the Liz wire, using the PDR.

Figure 5.1 shows the attempt to solder the ADXL337 using the Litz wire, using the PDR. For all further work following the vibration sensing E-yarn, the Litz wire has been used for all connections due to its durability and because high salinity environments (heavy sweating) have been seen to influence the E-yarns behaviour if only multistrand copper wires were used [15].

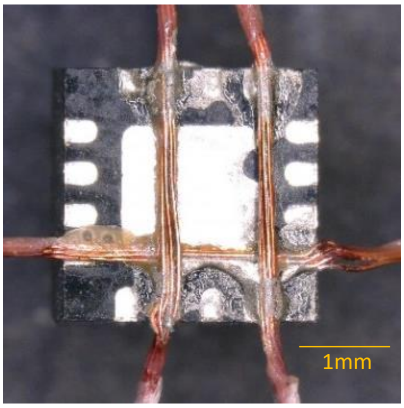


Figure 5.1 ADXL337 soldered using the PDR machine.

The microscope image of the ADXL337 shows that some connections are made but the y-axis is not soldered to the pad well. The other connections are not mechanically strong and once they are cut, they tended to fall off. This is not due to operator error or incorrect settings. It is because of the how they wires are placed on top of each other, restricting good physical connection with the solder pad. This can also be seen in Figure 5.2 with the ADXL345.

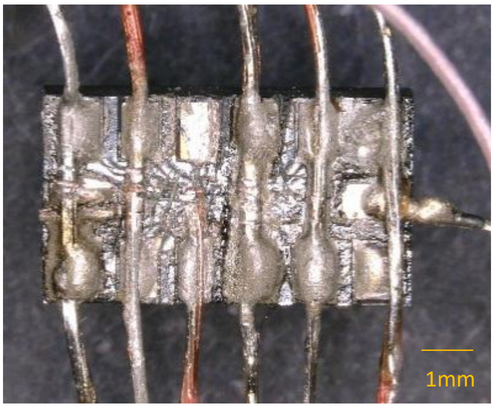


Figure 5.2 ADXL345 soldered using the PDR machine.

To combat this issue, a small PCB was designed to ease the soldering process. The board was designed using DipTrace (Dniepropetrovsk, Ukraine) and printed and cut at NTU. Figure 5.3 shows an example board for the ADXL345 along with the ADXL345 being connected to the PCB. The ADXL345 was connected to the board using conductive glue (CW2400 Liquid Adhesive, Chemtronics, Kennesaw, GA, USA).

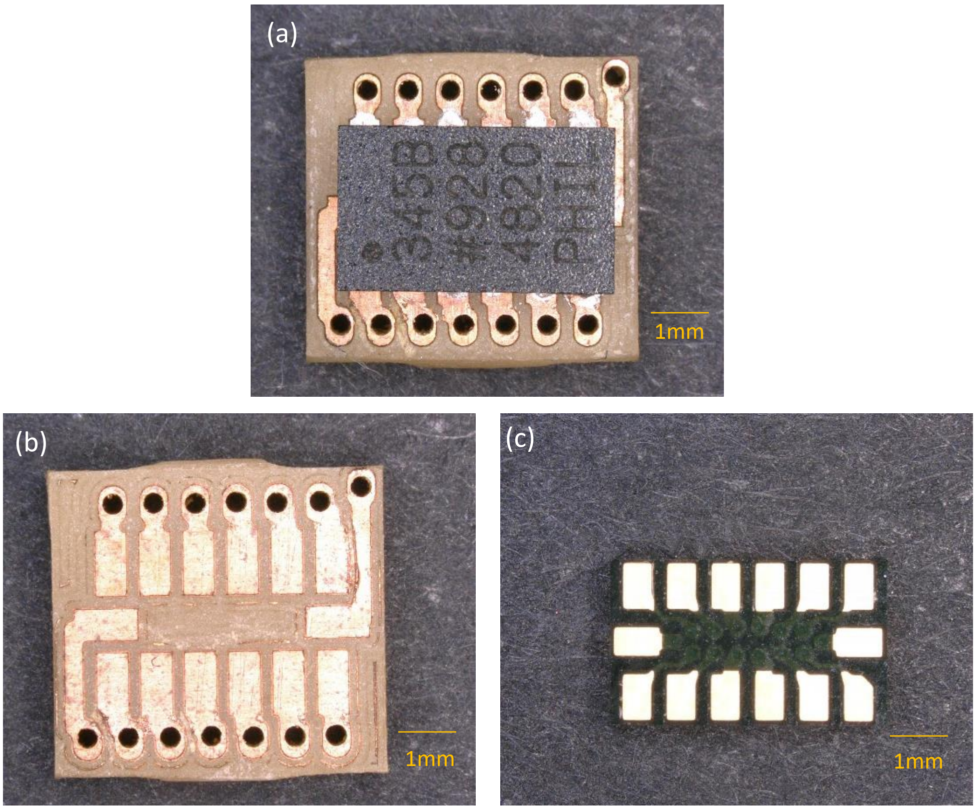


Figure 5.3 Microscope images. (a) ADXL345 glued onto the PCB, (b) PCB for the sensor to create an E-yarn and (c) the sensor ADXL345 for the PCB.

In Figure 5.3a it is impossible to tell if the glue had connected multiple solder pads together because of the small size. An alternative to the conductive glue to use conductive tape (3M 1245 Conductive Metallic Tape, 3M, Minnesota, United States). Conductive tape solved the issue of the solder pads being connected to each other as it only conducts in one direction. In the end, it was very difficult to solder the Litz wire to the PCB as it was one-side and very small. Additionally, the PCB adds extra thickness to the final E-yarn, which is undesirable aesthetically.

The final solution was that the Litz wire was directly soldered onto the sensor manually using a soldering iron. This was the method used to create the E-yarns containing the ADXL337 for gait measurement [4]. The development of E-yarns is still evolving, and this soldering technique was established concurrently with this study as part of the EPSRC grant mentioned in the acknowledgements section above. The author was involved in helping to develop this new technique and is acknowledged in the gait measurement article [4].

5.2.3 Testing of the E-Yarn

To understand the behaviour of the MPU-6050, ten pins were soldered with accoradnce to the datasheet. These inclcued pins 1, 8, 9, 10, 11, 13, 18, 20, 23 and 24. Pins 6, 7 and 12 were not required for the function of the sensor, as seen in the datasheet. Using a breadboard, the circuitry from the datasheet (Figure 5.4) was replicated to determine which pins and parts of the circuitry were essential. This was because E-yarns are manufactured in an unconventional way when compared to PCBs. It should be noted that previous E-yarns have been developed where less solder pads have been used [16]. Fewer solder pads are beneficial as there are less potential points of failure during the manufacurting process. Some sensors were broken between the soldering and encasultion stage due to wires breaking their connections with the solder pads.

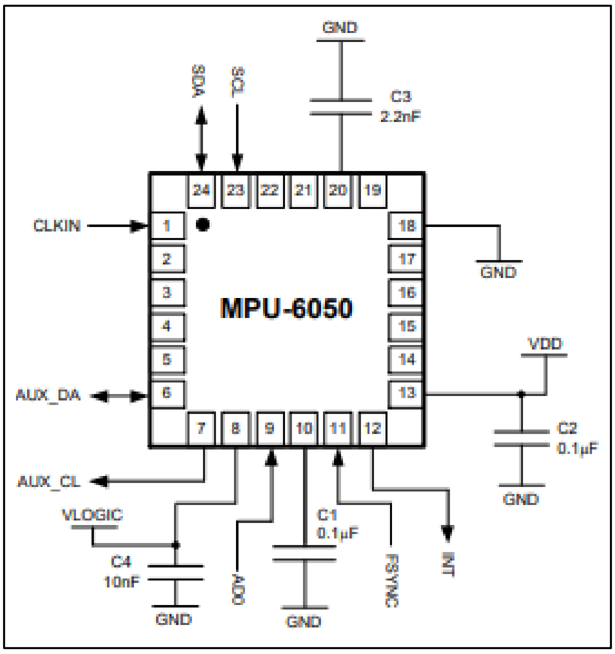


Figure 5.4: Circuitry for MPU-6050 taken from the datasheet [17]

The different pins and capacitors were removed one at a time to determine the functionally of the sensor. This was done to try to minimse the number of pins and componments as this is advantaguous for ease of manufacturing, durability and size of the final E-yarn and hardware. Whilst measuring the sensor output as the different pins and capacitors were removed, the sensor was kept still. This was because the solder pads are small, which resulted in a weak mechanical bond, meaning the wires could be pulled off easily. These tests showed that only seven pins were needed, 8, 9, 10, 13, 18, 23 and 24. Therefore, multiple sensors were soldered, to be turned into E-yarns.

The second step involved the encapsulation of the soldered IMU and a supporting Vectran™ yarn (Kuraray, Tokyo, Japan) within a UV curable resin (Dymax 9001-E-V3.5; Dymax, Corporation, Torrington, CT, USA) micro-pod (4 x 4 x 1 mm box). A silicone mold, slightly larger than the MPU-6050 was used to form the micro-pod. The Litz wires were all positioned in one direction parallel to the Vectran™ yarn as all the wires needed to go in the same direction, to the hardware module (see Figure 5.5c). The final step in the manufacturing process required the encapsulated IMU, along with the wires and Vectran™, to be covered in a braided sheath to consolidate the final yarn and add strength. This was achieved using a braiding machine (lay length = 5; RU1/24-80, Herzog GmbH, Oldenburg, Germany) and 24 polyester yarns (36 f/167 dtex; Ashworth and Sons, Cheshire, UK). This resulted in a final E-yarn that was 5.4 mm at its widest point that was mechanically robust and had the appearance of a textile yarn (see Figure 5.5d).

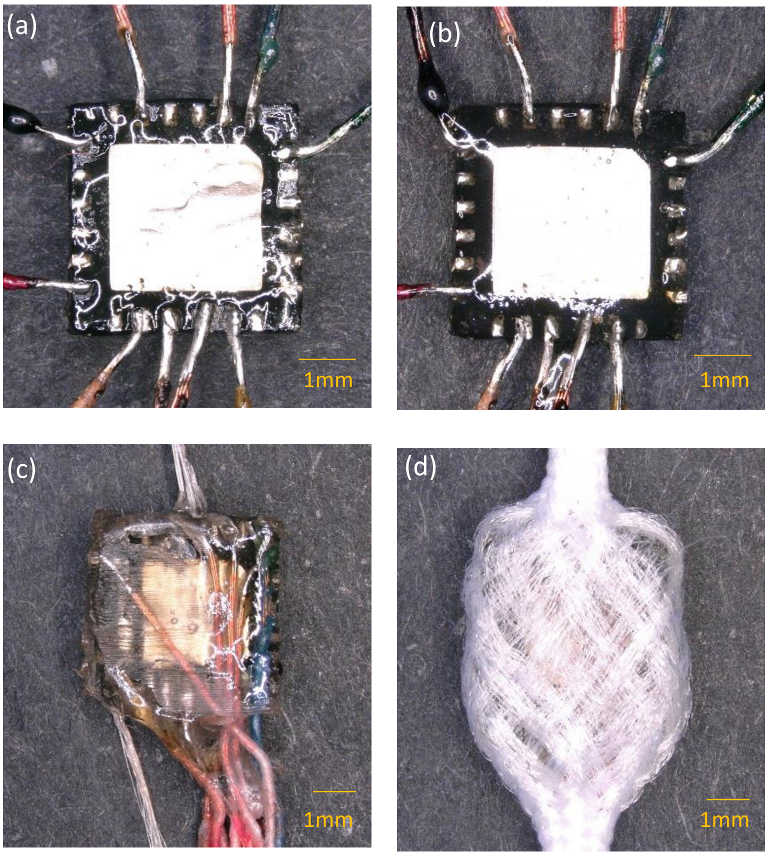


Figure 5.5 Images of the final sensor at the different stages of manufacturing process. (a) shows ten solder joints that was used in the final design, (b) shows the sensor with resin to protect the solder pads, (c) shows the sensor encapsulated with resin along with Vectran and (d) shows the sensor in final E-yarn form. Modified from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

The structure of the fibre braid was tight around the micro-pod and previous work exploring vibration transmission through yarns indicated that such a structure would have a negligible effect on the transmission of vibration [6]: hence, it was not expected that the yarn structure would influence the recorded motion data providing that tight textile structures were utilised. Regardless, the yarns were tested at each stage of the production process to ensure that they functioned in all dimensions at each stage (as breakages between the wires and solder pads could occur). This involved positioning the device relative to gravity and rotating the device at a known velocity (1.96 ± 0.12 rad/s) using a custom apparatus shown in Figure 5.6. This was done to give a constant repeatable value to compare the different E-yarns. The box on which the E-yarn is attached was used to position the sensor in the direction required.

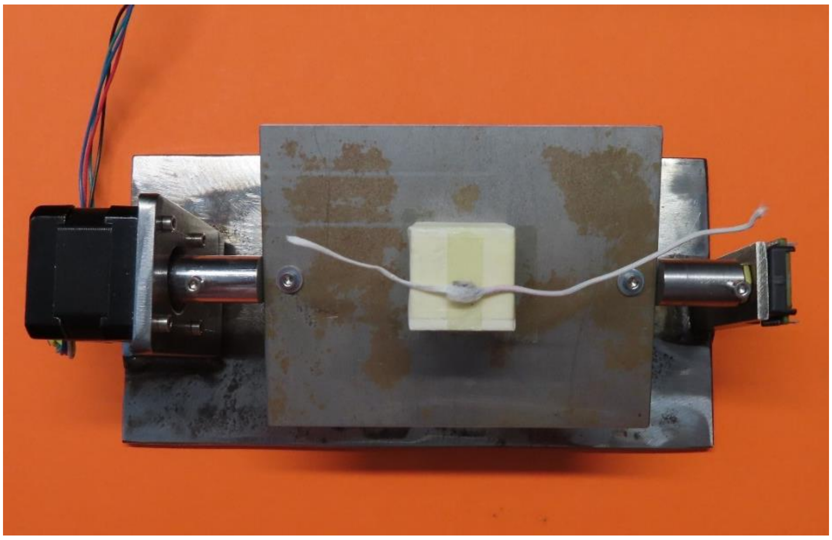


Figure 5.6 Testing apparatus for angular velocity

During the testing of the seven wire E-yarn, it was observed that the angular velocity in the z-axis was not being measured. This was not previously identified because the sensor had been kept still, and the angular velocity in the z-axis appeared to behave like the x and y axes. The final sensor ended up having ten pins soldered and used the circuit diagram provided by the supplier (shown in Figure 5.4). The new yarns were tested at each stage of the production process (after soldering, after encapsulation, after braiding) to ensure that they functioned in all dimensions at each stage (as breakages could occur). This test was performed on four yarns for all the stages in the process, as well as embedded with the over-sock.

The over-sock was seamlessly knitted using three yarns (Stretchline 20/DCY Black N66 DD / 78/2 N6, Stretchline 16/SCY Black 60/60 N66, and Nylon6 70/68/2 Black) on a Stoll ADF 3 E7.2 knitting machine (Lengede, Germany). The over-sock included a knitted channel for the E-yarn to be inserted as well as a small, knitted pocket (30 × 60 mm) for the hardware unit (used to communicate with the embedded IMU and collect data) shown in Figure 5.7.

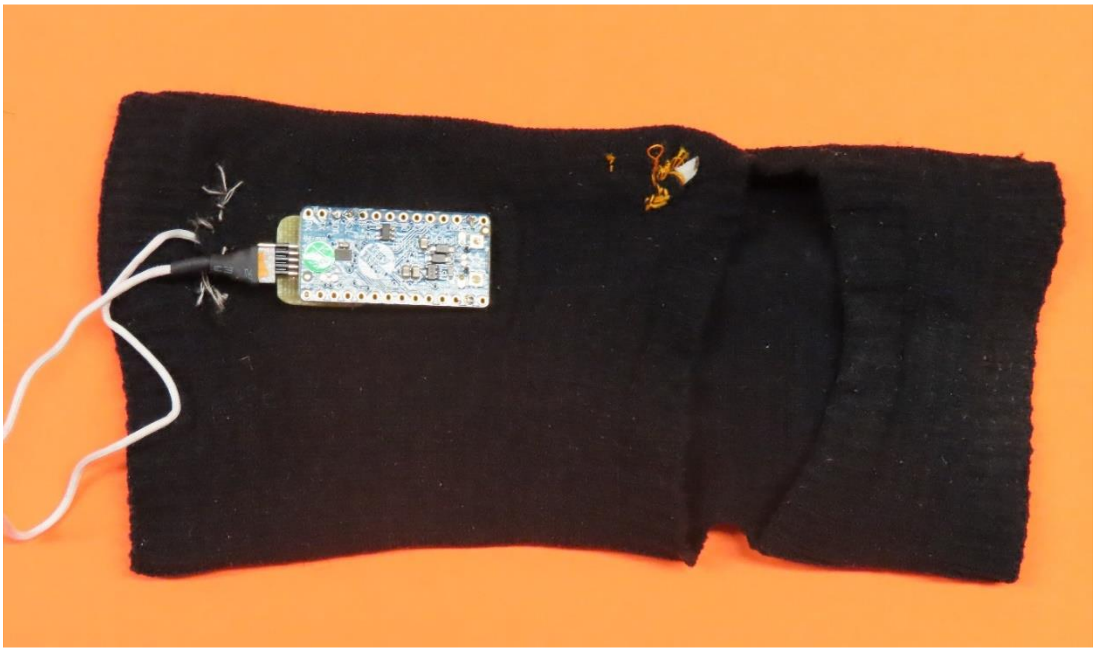


Figure 5.7 Image of the over-sock with the E-yarn embedded inside the channel and the hardware showing where the pocket is. Modified from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

The over-sock that was designed and presented in Chapter 4 had non-functioning E-yarns integrated within the channel. However, when the function E-yarns were integrated within the over-sock, channel was too tight. Therefore, the E-yarns were forced into the channel and tugged back out. Unfortunately, yarn 9 broke in this process. Ultimately, the design of the over-sock was altered to include a wider channel and the pocket was moved to be vertical and directly above the E-yarn. Table 5.2, Table 5.3 and Table 5.5 show the results of the E-yarn testing experiments for the soldered stage to insertion into the over-sock. Table 5.4 does not contain measurements whilst embedded within the over-sock, as yarn 9 was broken.

Table 5.2: Averaged data and standard deviation taken from yarn 7. Acceleration is measured in m/s^2 and angular velocity is measured in rad/s

	Soldered Stage	Encapsulated Stage	Yarn Stage	Embedded in Sock
Acceleration x-axis positive	9.73 ± 0.43	9.41 ± 0.35	9.61 ± 0.16	9.71 ± 0.11
Acceleration x-axis negative	-10.20 ± 0.25	-10.08 ± 0.45	-9.88 ± 0.18	-9.55 ± 0.08
Acceleration y-axis positive	9.75 ± 0.26	9.59 ± 0.37	9.77 ± 0.13	9.87 ± 0.09
Acceleration y-axis negative	-10.15 ± 0.38	-9.85 ± 0.33	-9.77 ± 0.13	9.28 ± 0.04
Acceleration z-axis positive	7.88 ± 0.18	8.09 ± 0.21	9.19 ± 0.07	9.28 ± 0.04
Acceleration z-axis negative	-11.82 ± 0.12	-11.29 ± 0.16	-10.49 ± 0.07	-10.03 ± 0.05
Angular velocity x-axis positive	2.08 ± 0.11		2.01 ± 0.09	1.83 ± 0.92
Angular velocity x-axis negative	-2.14 ± 0.11	-2.12 ± 0.10	-1.93 ± 0.13	-1.80 ± 0.36
Angular velocity y-axis positive	2.12 ± 0.12	2.13 ± 0.10	1.93 ± 0.09	2.42 ± 1.76
Angular velocity y-axis negative	-2.09 ± 0.09	-2.07 ± 0.09	-1.81 ± 0.12	-1.25 ± 0.95
Angular velocity z-axis positive	2.04 ± 0.13	2.05 ± 0.43	1.87 ± 0.10	1.92 ± 0.24
Angular velocity z-axis negative	-1.97 ± 0.09	-2.11 ± 0.11	-2.01 ± 0.12	-1.88 ± 0.80

Table 5.3 Averaged data and standard deviation taken from yarn 8. Acceleration is measured in m/s^2 and angular velocity is measured in rad/s

	Soldered Stage	Encapsulated Stage	Yarn Stage	Embedded in Sock
Acceleration x-axis positive	9.35 ± 0.49	9.38 ± 0.22	9.16 ± 0.11	9.40 ± 0.17
Acceleration x-axis negative	-10.29 ± 0.45	-10.35 ± 0.32	-9.61 ± 0.14	-9.48 ± 0.24
Acceleration y-axis positive	10.29 ± 0.43	10.27 ± 0.30	10.03 ± 10.22	9.60 ± 0.19
Acceleration y-axis negative	-9.53 ± 0.39	-9.45 ± 0.31	-9.53 ± 0.11	-9.31 ± 0.15
Acceleration z-axis positive	9.81 ± 0.22	9.70 ± 0.17	9.46 ± 0.07	9.41 ± 0.10
Acceleration z-axis negative	-10.09 ± 0.21	-9.96 ± 0.10	-9.73 ± 0.07	-10.14 ± 0.09
Angular velocity x-axis positive	1.94 ± 0.08	1.99 ± 0.10	1.88 ± 0.09	1.89 ± 0.10
Angular velocity x-axis negative	-2.16 ± 0.12	-2.17 ± 0.13	-1.99 ± 0.11	-2.00 ± 0.08
Angular velocity y-axis positive	1.91 ± 0.10	2.00 ± 0.10	1.87 ± 0.11	1.90 ± 0.26
Angular velocity y-axis negative	-2.10 ± 0.09	-2.11 ± 0.09	-1.82 ± 0.11	-1.97 ± 0.11
Angular velocity z-axis positive	1.88 ± 0.06	2.13 ± 0.11	1.98 ± 0.07	2.02 ± 0.11
Angular velocity z-axis negative	-1.91 ± 0.11	-2.14 ± 0.11	-1.98 ± 0.11	-1.97 ± 0.45

Table 5.4 Averaged data and standard deviation taken from yarn 9. Acceleration is measured in m/s^2 and angular velocity is measured in rad/s

	Soldered Stage	Encapsulated Stage	Yarn Stage
Acceleration x-axis positive	9.45 ± 0.43	9.56 ± 0.44	9.67 ± 0.13
Acceleration x-axis negative	-10.52 ± 0.37	-10.09 ± 0.35	-9.71 ± 0.13
Acceleration y-axis positive	10.12 ± 0.29	10.18 ± 0.20	9.92 ± 0.13
Acceleration y-axis negative	-9.56 ± 0.49	-9.47 ± 0.57	-9.67 ± 0.14
Acceleration z-axis positive	8.16 ± 0.24	10.17 ± 0.23	9.05 ± 0.07
Acceleration z-axis negative	-9.48 ± 0.25	-10.33 ± 0.21	-10.63 ± 0.07
Angular velocity x-axis positive	1.88 ± 0.08	1.87 ± 0.59	2.02 ± 0.10
Angular velocity x-axis negative	-1.89 ± 0.11	-1.96 ± 0.11	-2.03 ± 0.14
Angular velocity y-axis positive	1.91 ± 0.10	2.07 ± 0.09	2.03 ± 0.10
Angular velocity y-axis negative	-1.75 ± 0.08	-1.84 ± 0.09	-1.92 ± 0.11
Angular velocity z-axis positive	1.77 ± 0.10	1.84 ± 0.10	1.95 ± 0.11
Angular velocity z-axis negative	-1.70 ± 0.08	-1.76 ± 0.09	-1.91 ± 0.11

Table 5.5 Averaged data and standard deviation taken from yarn 10. Acceleration is measured in m/s^2 and angular velocity is measured in rad/s

	Soldered Stage	Encapsulated Stage	Yarn Stage	Embedded in Sock
Acceleration x-axis positive	10.18 ± 0.35	10.12 ± 0.18	9.74 ± 0.12	9.54 ± 0.09
Acceleration x-axis negative	-9.70 ± 0.47	-9.70 ± 0.21	-9.71 ± 0.14	-9.79 ± 0.11
Acceleration y-axis positive	10.50 ± 0.38	6.38 ± 0.86	9.83 ± 0.11	9.80 ± 0.10
Acceleration y-axis negative	-9.23 ± 0.34	-9.19 ± 0.36	-9.65 ± 0.12	-9.37 ± 0.09
Acceleration z-axis positive	8.46 ± 0.21	8.36 ± 0.18	8.50 ± 0.06	8.78 ± 0.06
Acceleration z-axis negative	-11.42 ± 0.24	-11.38 ± 0.17	-11.10 ± 0.06	-11.11 ± 0.05
Angular velocity x-axis positive	2.19 ± 0.13	2.12 ± 0.12	1.78 ± 0.12	1.89 ± 0.33
Angular velocity x-axis negative	-2.18 ± 0.13	-2.15 ± 0.12	-1.88 ± 0.10	-1.11 ± 1.16
Angular velocity y-axis positive	2.15 ± 0.11	2.14 ± 0.12	1.89 ± 0.13	0.19 ± 1.62
Angular velocity y-axis negative	-2.16 ± 0.12	-2.02 ± 0.12	-1.93 ± 0.11	-2.00 ± 0.33
Angular velocity z-axis positive	2.07 ± 0.13	2.16 ± 0.10	1.99 ± 0.12	1.54 ± 0.45
Angular velocity z-axis negative	-2.04 ± 0.10	-2.10 ± 0.12	-2.02 ± 0.12	-1.92 ± 0.17

In all cases the yarn production process had a negligible effect on the sensor performance. However, it should be noted that there were relatively large differences in readings from sensor to sensor (for example, for yarn 7 in the z-axis acceleration under gravity = 7.87 – 9.28 m/s^2). It was believed that this was due to the tolerances of the sensor as well as the positioning. Additionally, for yarn 10, at the encapsulated stage, the y-axis acceleration under gravity measured 6.38 m/s^2. Whilst it was measuring 6.38 in the y-axis, it was also measuring -9.27 in the z-axis, implying that the sensor moved. As the sensor was taped to the box, shown in Figure 5.6, it must have detached during the experiments. The angular velocity measurements taken whilst using the over-sock were inconsistent as the over-sock altered the velocity of the yarn due to its weight. This is most apparent when looking at the data from yarns 7 and 10.

Ultimately, differences in the absolute values recorded were not perceived as being an issue as in both the visual analysis and deep learning analysis of the motion data relative changes are identified (shown in Section 5.5). It is important to highlight that looking at relative measurements removed certain operational considerations for using the over-sock including hysteresis in the textile once the sock is put on (affecting the precise positioning of the sensor and potentially absolute measurements) and manufacturing tolerances.

5.3 Hardware Development

5.3.1 Microcontroller

The initial experiments to determine which pins and components were required for the operating circuit, used a breadboard. The breadboard was used to make the operating circuit and connect it to an Arduino Uno (Somerville, MA, US). The Arduino Uno was obviously too big to be used for any wearable designs but was a practical solution for benchtop testing. Based on the focus group it was apparent that the smaller the hardware module the better. Smaller hardware is less visible and more comfortable.

Whilst testing the functionality of the yarns during the manufacturing process, an ItsyBitsy nRF52840 (Adafruit Industries, New York, USA) was used. This was chosen as it is small and contains a Bluetooth module that allows for wireless transfer for data. Along with the ItsyBitsy, the same breadboard was used for all benchtop testing.

For the human trials, the original plan was to use a Feather M0 Adalogger (Adafruit Industries, New York, USA) that used an SD card. Due to previous issues with Bluetooth during the pilot study presented in Chapter 2, it was decided that an SD card would ensure complete data collection. In addition, this is the microcontroller that Adafruit recommend when buying the MPU-6050 breakout board. Furthermore, the Feather contains power management within the board. Although it is larger than the ItsyBitsy, it would have meant that a power management board would not be needed when using a battery. Furthermore, the Feather M0 Adalogger has an equivalent microcontroller that contains a Bluetooth module rather than the SD card (Feather M0 Bluefruit LE). The addition of Bluetooth is useful for a final device, but this research was to create a proof-of-concept and Bluetooth was not essential.

Unfortunately, although the Feather worked to control the breakout board, when connected to an E-yarn using the PCB with the connector as well as the switch and the battery, the E-yarn could not connect to the Arduino programme being used. Figure 5.8 shows an image of the Feather M0 Adalogger with the PCB, switch and battery attached. This is most likely due to the power management board not powering the E-yarn correctly. Consequently, the ItsyBitsy (Figure 5.9) was used for the human trials, and it was wired to the laptop.

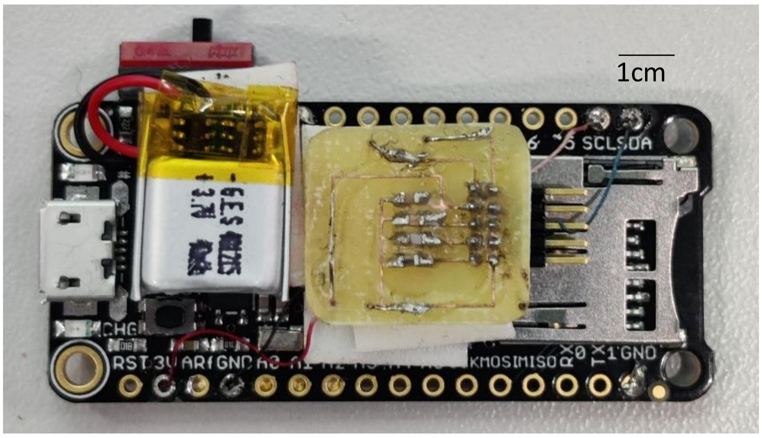


Figure 5.8 Feather M0 Adalogger with battery, switch and PCB.

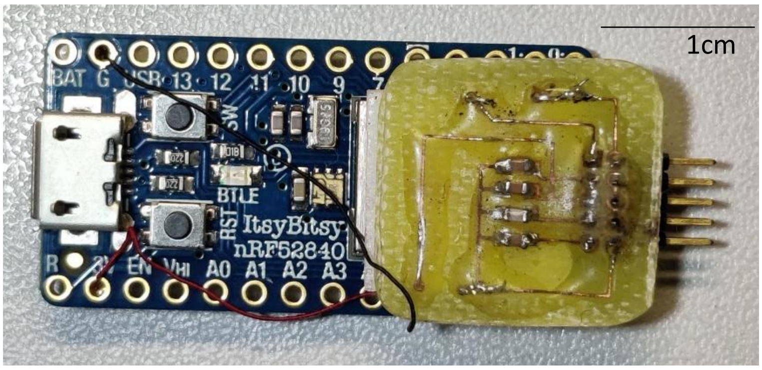


Figure 5.9 ItsyBitsy with PCB, used for human trials.

5.3.2 Operating Circuit PCB

As the breadboard could not be used for the human trials, an operating circuit PCB was designed using DripTrace and made at Nottingham Trent University. Due to the limitation of the facilities available, the board was made slightly larger than desired, however, it was still only 1.5cm x 1.5cm. The board contains room for four capacitors (size 0603), a connector (20021112-00010T4LF, Amphenol Communications Solutions, Wallingford, Connecticut, USA) and four holes for wires to connect to the microcontroller. Figure 5.10 shows the PCB before anything was soldered onto it. Once everything was soldered to the PCB, it was covered in resin to protect each component and the solder joints.

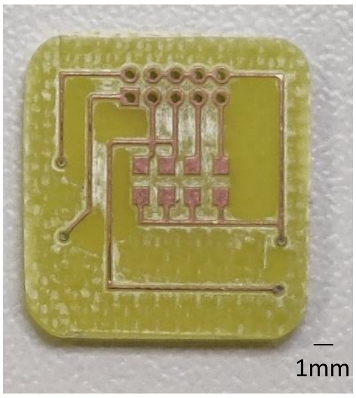


Figure 5.10 PCB used to connect the wires from the E-yarn to the microcontroller.

5.3.3 Connector

The E-yarn had a connector soldered onto the end (20021311-00010T4LF, Amphenol Communications Solutions, Wallingford, Connecticut, USA) to allow for the removal of the supporting hardware for washing. This connector was selected as it was the smallest available that included ten pins for each wire coming from the E-yarn. Furthermore, it allowed the hardware to be removed to be charged, and potentially replaced if needed. A standard 10 pin connector was used, the pins on the connector were encapsulated in UV curable resin to prevent any short circuits as the pins were malleable, shown in Figure 5.11.

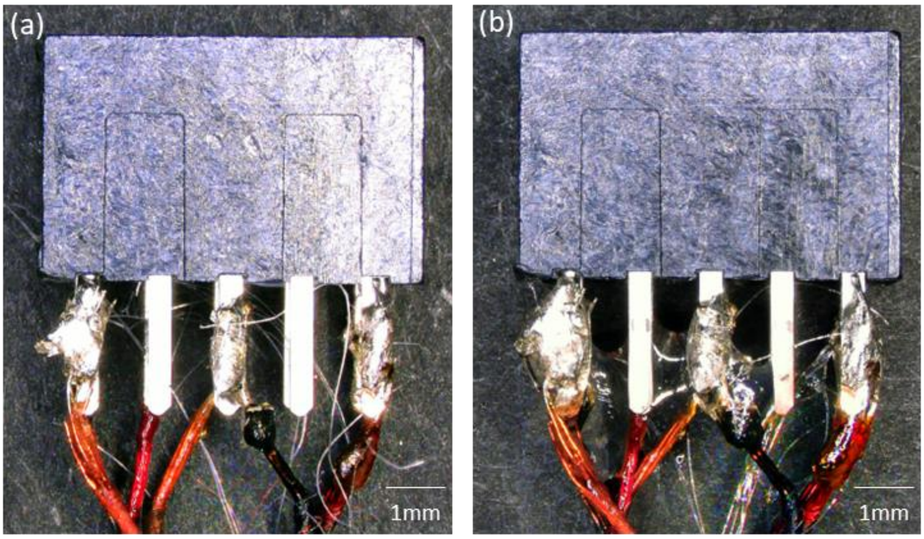


Figure 5.11 (a) Connector with wires from the E-yarn soldered on and (b) Connector with wires from E-yarn soldered on with resin

The connector needed extra protection and to provide a neat finish, for this, two types of covering were explored. A mould was made to cover the connector in silicone. This was tried and dismissed as the silicone was too heavy, large and not aesthetically pleasing (Figure 5.12).

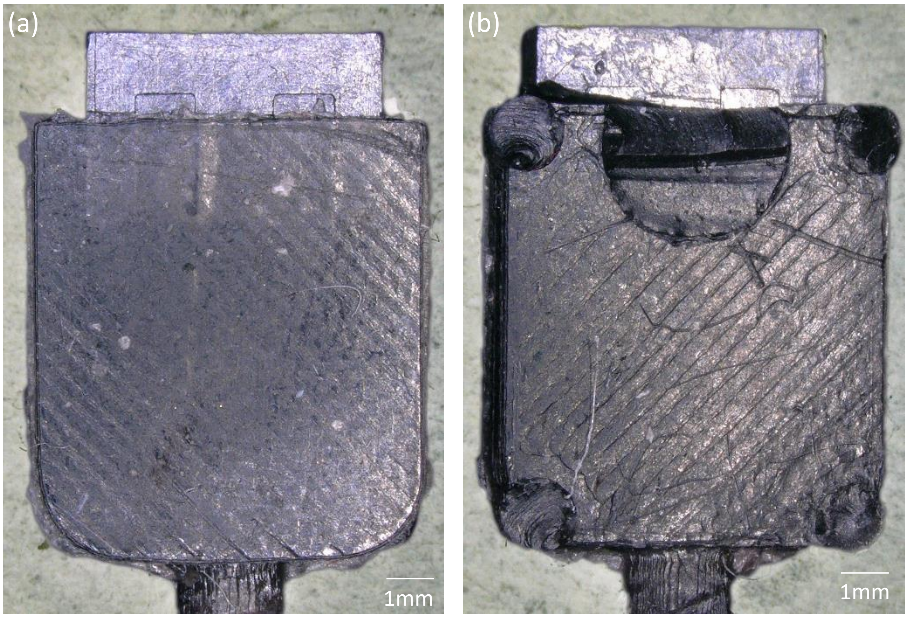


Figure 5.12 Silicone covering of the connector (a) top side and (b) bottom side

Ultimately the connector was covered using heat shrink to protect the connector (Figure 5.13).

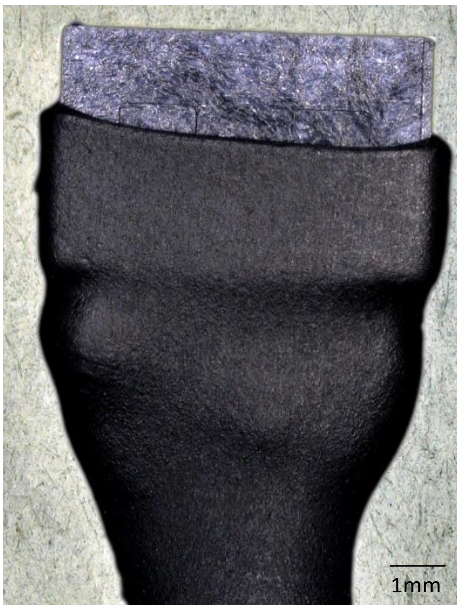


Figure 5.13 Connector covered with heat shrink

5.4 METHODS FOR THE HUMAN TRIALS

5.4.1 TESTING PROTOCOL

5.4.1.1 PARTICIPANTS

For the human trials of the over-sock thirteen healthy female volunteers, aged between 22-33 were recruited. Their heights ranged from 1.57 m to 1.72 m and their weights ranged from 50 kg to 109 kg. Ethical approval was provided from the Nottingham Trent University Schools of Art and Design, Architecture, Design and Humanities Research Ethics Committee. Informed consent was obtained by all the participants before the study.

5.4.1.2 ACTIVITIES

Each participant was asked to perform seven activities, repeated ten times: walking with a turn, sit-to-stand from a chair, 'Timed Up and Go', a controlled stumble, and three types of falls onto a crash mat fall (sideways, backwards, and frontwards). Walking and the ability stand from a seated position were chosen as they mimic basic ADLs [18]. Further details on ADLs are provided in Chapter 3. The 'Timed Up and Go' tests were included as they are used by clinicians for fall risk assessments [19]. The controlled stumble was included to simulate a near-fall. For the near-fall, each participant was given the freedom to choose how and when to stumble. They all interpreted the near-fall differently and performed the activity as they felt appropriate. Some walked then stumbled and stopped for each repeat. Others walked in a straight line, stumbled, and continued walking in a line. Finally, some walked around the room stumbled and continued to walk around the room, with no pauses. The data from the controlled stumble therefore varied significantly from participant to participant as each participant interpreted a stumble slightly differently. The three types of falls were performed to see if there were significant differences in the results for different falls and to provide data to balance the datasets. For the fall activities, the participants were stood directly next to the crash mat and fell onto the crash mat ten times. The data included each fall and each time the participants returned to a standing position. There was a pause before the participants fell, as they were lying down, and once they had returned to a standing position. The pause time varied between participants. The human trials were filmed so that movement could be easily identified in the data.

5.4.1.3 Data collection

An over-sock was worn on both the left and right foot. Contained within each over-sock was a motion sensing E-yarn along with its own set of hardware that was connected to a laptop using extended USB cables (see Figure 5.14b).

Data was collected using the Arduino 1.8.9 software (Somerville, MA, USA), at a 25 Hz sampling rate (informed by the pilot study and the literature [20]). The code for the microcontroller was developed using the Arduino Integrated Development Environment (Arduino, Turin, Italy). The Adafruit_MPU6050 library (by Adafruit) was utilized in this work [21]. The data was read-in using the Arduino IDE and was transferred to Microsoft Excel (Microsoft Corporation, Washington, USA) using the ArduSpreadsheet plug-in (developed by Indrek Luuk, available here [22]), with Excel used to create the graphs shown in Section 5.5.1 and Section 5.5.3. No filtering or signal processing of any kind was applied to the collected data.

Bluetooth was not used as during the previously mentioned pilot study this was observed to be unreliable [23], and it was important to ensure the full collection of the data. It was believed that this may have been partially due to signal interference in the room used for the study. A microcontroller board with Bluetooth capabilities was selected to easily allow the innovation to communicate wirelessly in the future, however developing this capability fully was beyond the scope of this pilot project.

Figure 5.14 Photographs of the over-sock. (a) The over-sock contained one motion sensing E-yarn as well as the supporting hardware unit contained within a pocket. (b) Over-socks being worn during testing. The USB cables were attached to the participants using a stretchable fabric to prevent unnecessary strain on the hardware unit. Modified from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

5.4.1.4 DATA ANALYSIS AND MACHINE LEARNING ALGORITHM

To classify the data gathered in this work, a deep learning classifier was used. The types of deep learning architecture that would be most applicable to the data in this work were those that were developed to classify time series data. One of the deep learning architectures that has been particularly adept at classifying time series data relating to movement and gait are variants of recurrent neural networks, more specifically BiLSTM's (Bi-directional long term short term memory network) [3–5]. Due to its previous success in classifying time series data, the same BiLSTM was used in this work: The architecture of the network that was used to classify the data can be seen in Table 5.6.

Table 5.6 Illustration of the bi-directional long term short term memory (BiLSTM) network topology used to classify the data in this work. Taken from [1]; this table is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

Sequence input layer
Dropout layer
BiLSTM layer (200 nodes)
Dropout layer
ReLU layer
Fully connected layer
Softmax Layer
Output Layer

The raw data collected from the sensors was fed directly into the network. The data was then split into data instances consisting of 200 timesteps (the timestep being an instance of data gathered at a specific time) which were sampled at intervals of 20 timesteps. The data was not down-sampled at this stage; collectively the data instances covered all of the timesteps (i.e. the first data instance represented timesteps 1-200, the second 21-220, and so on). This aimed to ensure that a large volume of the features were present within the data, without generating excessive volumes of data. In total, this generated 17,138 data instances over all of the ADL's. This was randomly down sampled for all experiments to achieve a class balance between the ADL's, except for the work in Figure 5.17, where it was important to understand how all of the ADL's were classified. The data was split approximately into 75% training, 12.5% validation and 12.5% testing data (which is the data available in the confusion matrices). The testing/validation data used was from three participants of the cohort, and the remaining data was used for training. This was to best ensure the real-world applicability of this work by testing the network on participants that were not involved in the training data. The networks were trained for a maximum of 50 epochs, or when the performance of the validation data had not improved for 10 subsequent epochs. The ADAM optimizer was used with a minibatch size of 128.

Results from the trained model are presented as confusion matrices: A confusion matrix is a visual representation of the performance of the algorithm. The column on the far right of the plot shows the percentages of all the examples predicted to belong to each class that are correctly and incorrectly classified. These metrics are often called the precision (or positive predictive value) and false discovery rate, respectively. The row at the bottom of the plot shows the percentages of all the examples belonging to each class that are correctly and incorrectly classified. These metrics are often called the recall (or true positive rate) and false negative rate, respectively. The cell in the bottom right of the plot shows the overall accuracy. The values in the centre of the matrix (red and green boxes) relate to classification with respect to the complete dataset and are used to determine the precision and recall.

5.5 RESULTS AND DISCUSSION OF THE HUMAN TRIALS

5.5.1 VISUAL REPRESENTATION OF THE DATA

The collected data was first interpreted visually as shown in Figure 5.15 and Figure 5.16. The data appeared to show similar pattens between each participant and for both feet (full datasets are available in the publicly available data-archive associated with the paper [24]. The ADL presented in Figure 5.15 shows data from the 'Timed Up and Go' test, which is a combination of the activities in the other two ADLs, and the data collected during a backwards fall are shown in Figure 5.16. The data used for these graphs was for the right foot of Participant 1.

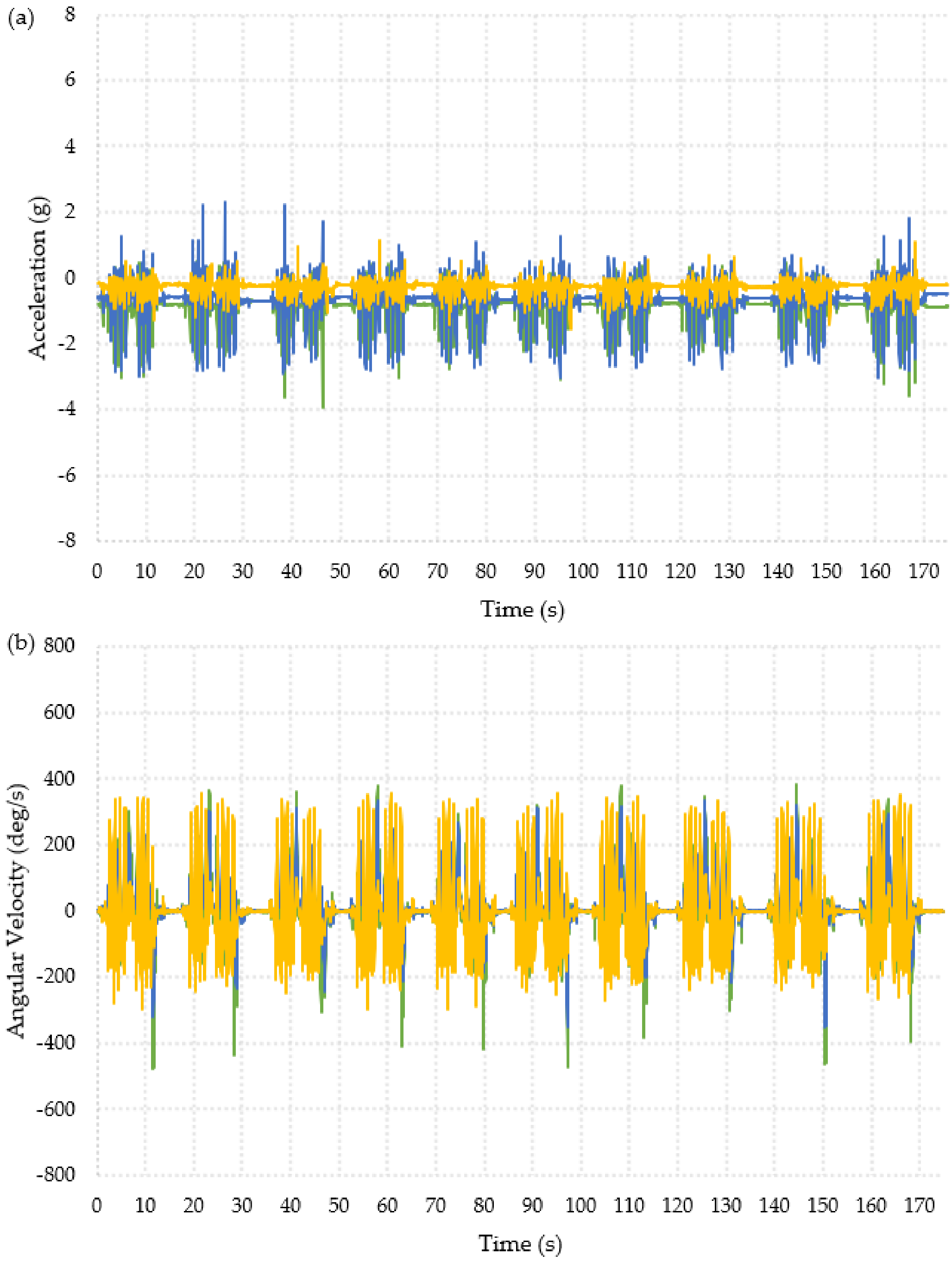


Figure 5.15 Graphical representation of the data collected from one foot for one participant during the 'Timed Up and Go' activity, ten repeats of the 'Timed Up and Go' are shown. X-axis = ——, y-axis = ——, z-axis = —— . (a) Acceleration. (b) Angular velocity. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

In Figure 5.15a, the acceleration data was visible when the participant was moving compared to when they were still. The turns were also visible in Figure 5.15b, where there were two per repeat activity; this can be seen by looking at changes in the x- and y-axes. The second turn before the participant sat back down had the largest change in angular velocity, about -430 deg/s in the x-axis and 350 deg/s in the y-axis. The turns are masked within the acceleration data due to the walking motion. The sit-to-stand activity cannot be seen in the data visually.

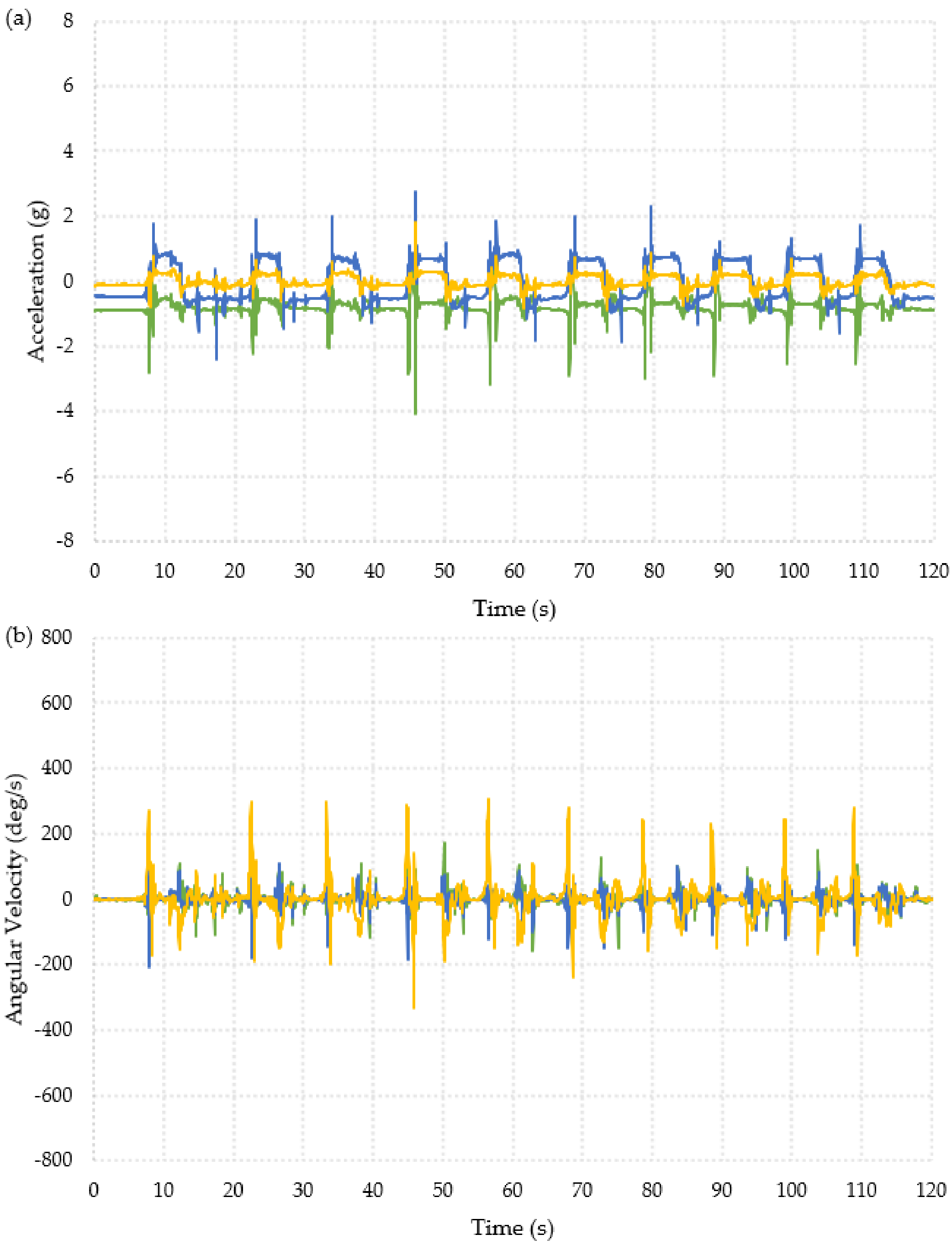


Figure 5.16 Graphical representation of the data collected from one foot for one participant during the backwards fall activity. X-axis = ——, y-axis = ——, z-axis = ——. Ten repeated falls are shown. (a) Acceleration. (b) Angular velocity. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

The ten falls can clearly be seen from the acceleration data shown in Figure 5.16a. There was a change in acceleration in all three axes. From the first fall there was an initial decrease in the x-axis of 1.95 g followed by an increase of 1.2 g. The y- and z-axes showed an increase in the acceleration of around 1.3 g and 0.5 g respectively. Figure 5.16b showed an increase in the angular velocity in the z-axis with a maximum increase of about 299 deg/s at the point of the fall. There was also a decrease in the x-axis and y-axis angular velocity at the point of the fall. The x-axis decreases varied between 40 and 80 deg/s and the y-axis decrease varied between 100 and 200 deg/s.

The patterns in Figure 5.15 and Figure 5.16 clearly showed very different behaviour for each activity and this might allow for thresholds to be defined to identify falls.

5.5.2 Using a Machine Learning Algorithm to Identify Falls

The collected data was used to train a deep learning model in the interests of accurately classifying the different activities. Full datasets were used in the model and therefore the data included the pauses between each repeat for the ADLs and the participant getting back up after each fall. The stumble data did not have a strict pattern as each participant did this activity differently. Some stumbled then paused, others walked in a line stumbled and turned, whilst some walked around the room and stumbled as they moved.

Figure 5.17 shows the confusion matrix generated when acceleration and angular velocity data from both feet was used. This data represents all 13 participants.

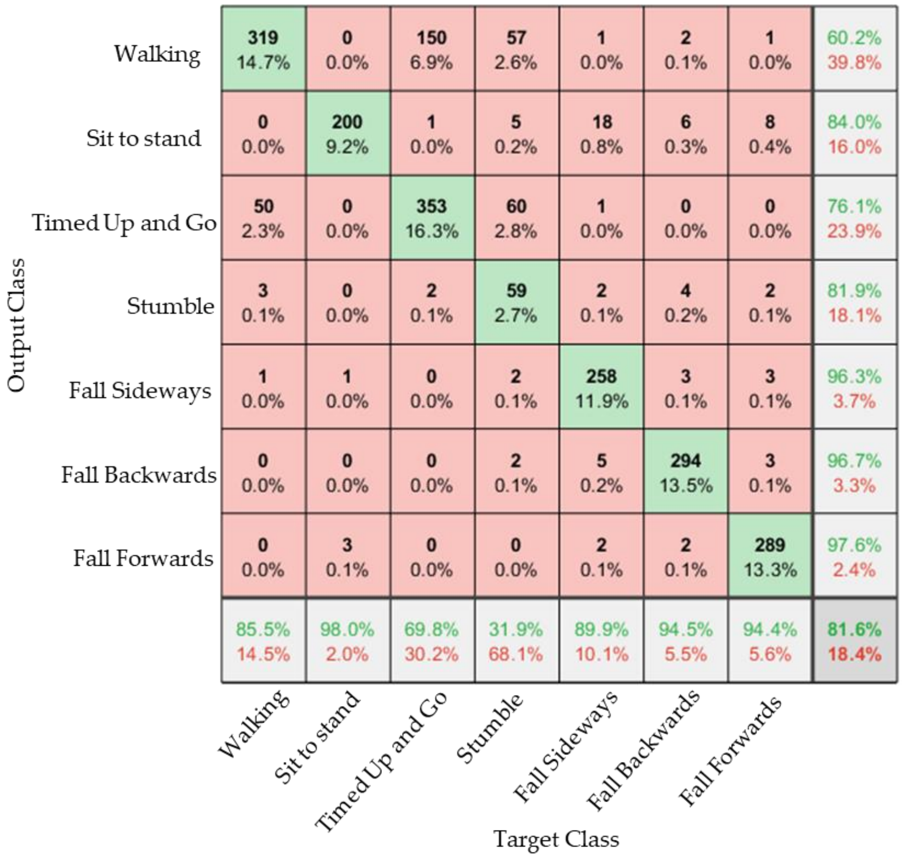


Figure 5.17 Confusion matrix classifying all of the activities performed for the data collected from all of the participants. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

From Figure 5.17, an overall classification accuracy of 81.6 % was observed. This also showed that the algorithm can easily classify between the ADLs and falls. It was seen that the controlled stumble activity was the hardest to classify, which was to be expected. The data used to create the confusion matrix included all of the data for all of the participants. However, the fall acceleration data for Participant 10 was incomplete, and the sensor appeared to have broken during this trial. As the participant did not wish to repeat the fall experiments, this could not be repeated. Therefore, the other confusion matrices present below were created without Participants 10's data and without the stumble. The confusion matrices below were trained using data from nine participants and tested on three participants.

Output Class \ Target Class	Walking	Sit to stand	Timed Up and Go	Fall Sideways	Fall Backwards	Fall Forwards	
Walking	394 17.6%	0 0.0%	244 10.9%	0 0.0%	2 0.1%	4 0.2%	61.2% 38.8%
Sit to stand	0 0.0%	185 8.3%	11 0.5%	3 0.1%	2 0.1%	5 0.2%	89.8% 10.2%
Timed Up and Go	34 1.5%	0 0.0%	313 14.0%	0 0.0%	0 0.0%	1 0.0%	89.9% 10.1%
Fall Sideways	3 0.1%	55 2.5%	2 0.1%	310 13.8%	5 0.2%	0 0.0%	82.7% 17.3%
Fall Backwards	0 0.0%	4 0.2%	0 0.0%	25 1.1%	310 13.8%	0 0.0%	91.4% 8.6%
Fall Forwards	1 0.0%	4 0.2%	1 0.0%	13 0.6%	2 0.1%	306 13.7%	93.6% 6.4%
	91.2% 8.8%	74.6% 25.4%	54.8% 45.2%	88.3% 11.7%	96.6% 3.4%	96.8% 3.2%	81.2% 18.8%

Figure 5.18 Confusion matrix showing the results of the classification of the three ADL activities and three fall activities. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

Figure 5.18 shows that excluding Participant 10 and the stumble activity did not make a significant change to the overall accuracy of the model. An accuracy of 81.6 % was seen in Figure 5.17 and 81.2 % in Figure 5.18. The sideways fall could be classified with an accuracy of 88.3 % whereas the other two falls could be classified with accuracies of 96.6 % and 96.8 %; the reason for this discrepancy is unclear. It was also observed that there were some misclassifications between the 'Timed Up and Go' tests and walking activities, this was likely due to the similarities between the activities. Ultimately the point of the system was to classify between ADLs and the falls, so this confusion would not be a hindrance in implementing the device.

It was subsequently desirable to further understand what data was helpful in classifying between falls and ADLs. Nine conditions were explored looking at processing data from both feet individually (as well as together) and looking at all of the sensor data as well as the acceleration data, and angular velocity data individually. Figure 5.19 shows the confusion matrices from both feet.

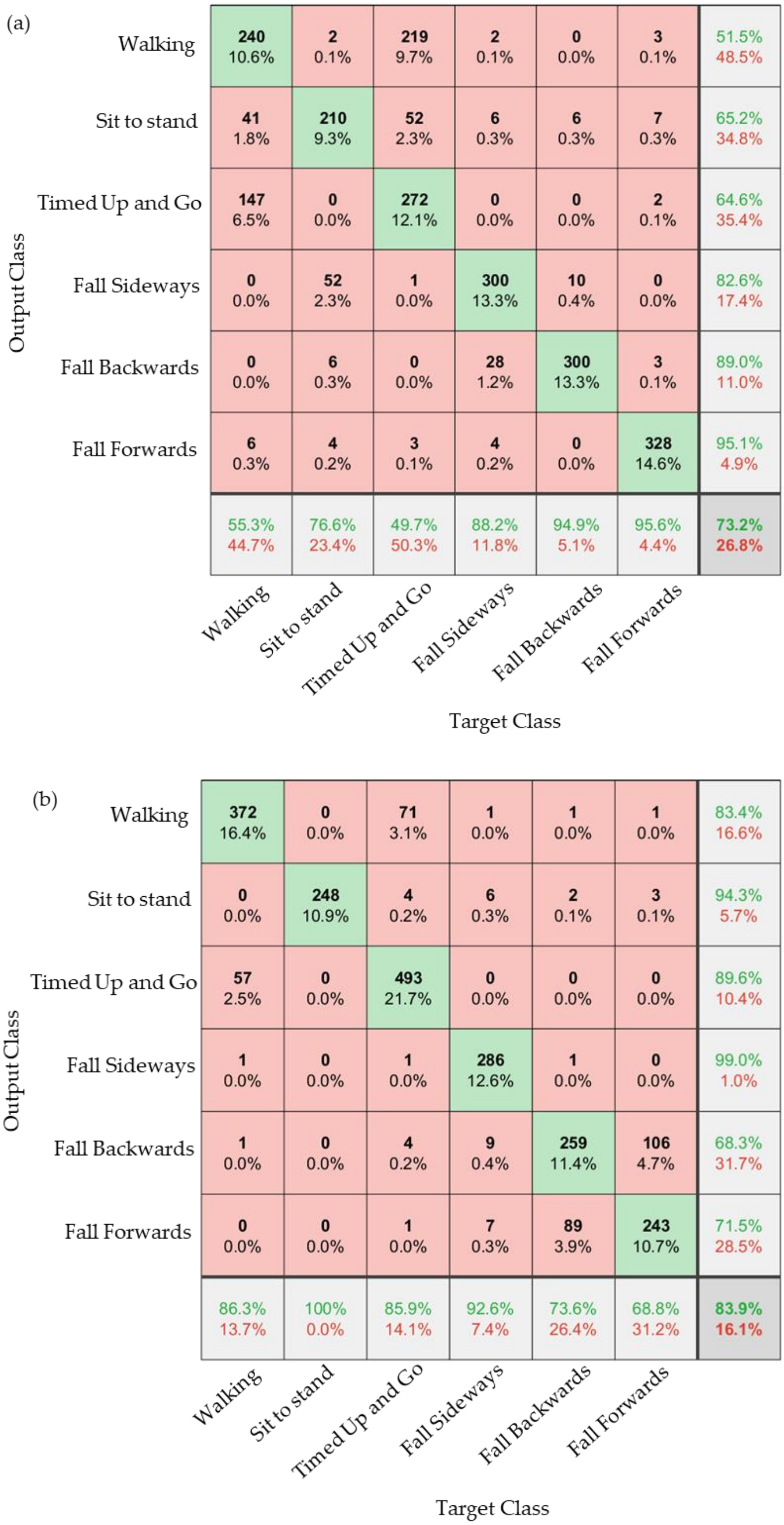
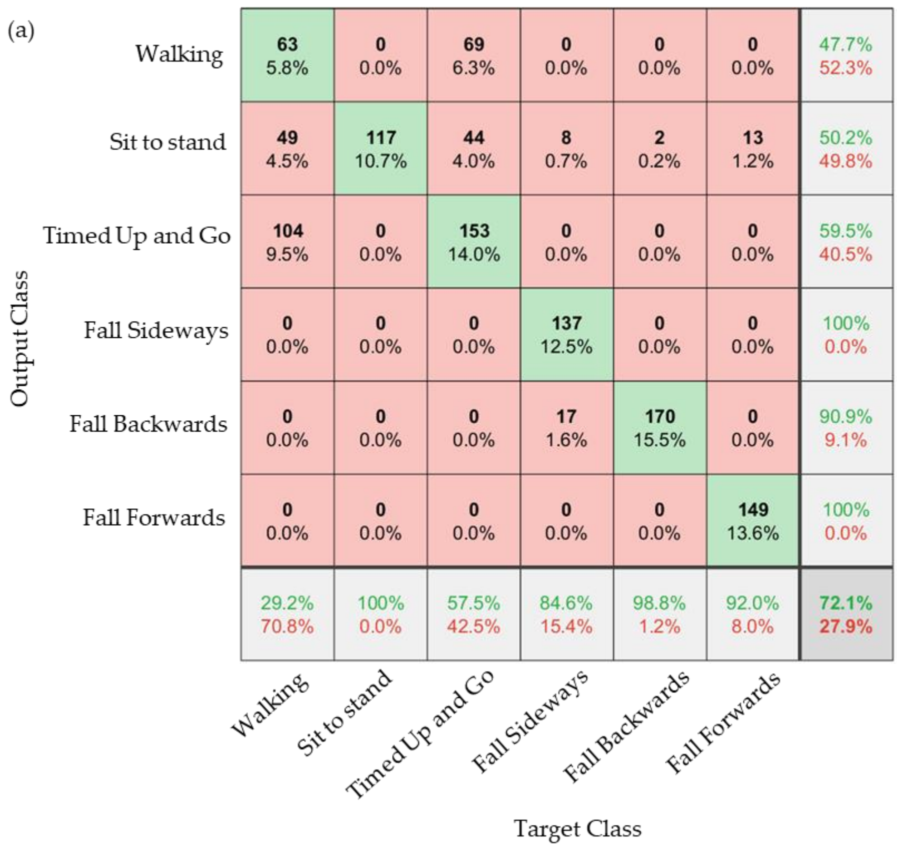


Figure 5.19 Confusion matrices for the data taken from both feet. (a) Acceleration data. (b) Angular velocity data.

The confusion matrix shows a higher accuracy of 83.9% when looking at the angular velocity data alone for both feet. However, the angular velocity data misclassifies the falls. As in Figure 5.18 there is misclassification between the ‘Timed Up and Go’ tests and the walking activity. The sit to stand was classified with 100% accuracy when looking at the angular velocity alone. This is most likely because during the activity the angle of the foot remains the same until the participant moves. Figure 5.20 shows the confusion matrices for the right foot only and Figure 5.21 shows the confusion matrices for the left foot only.



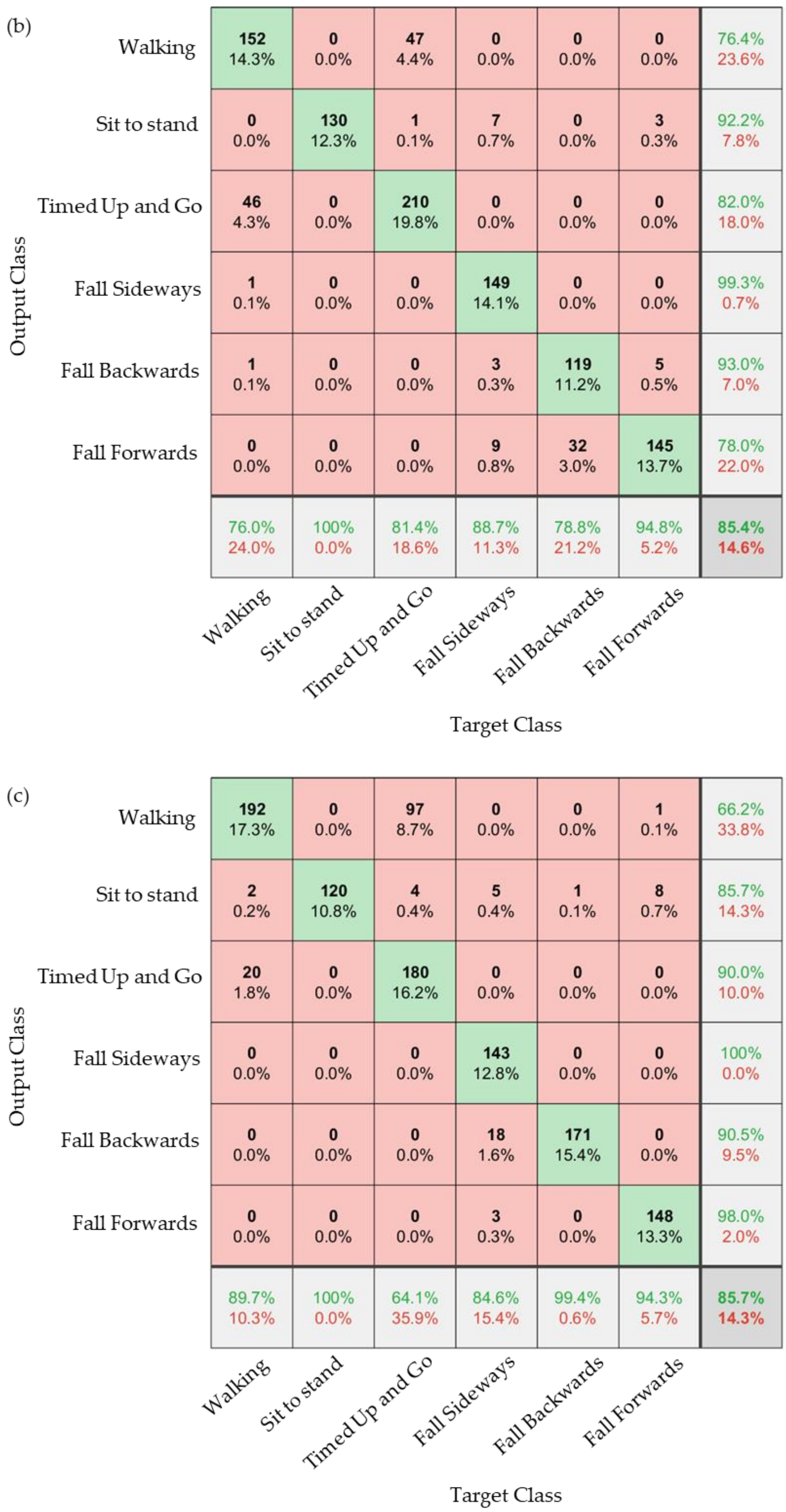
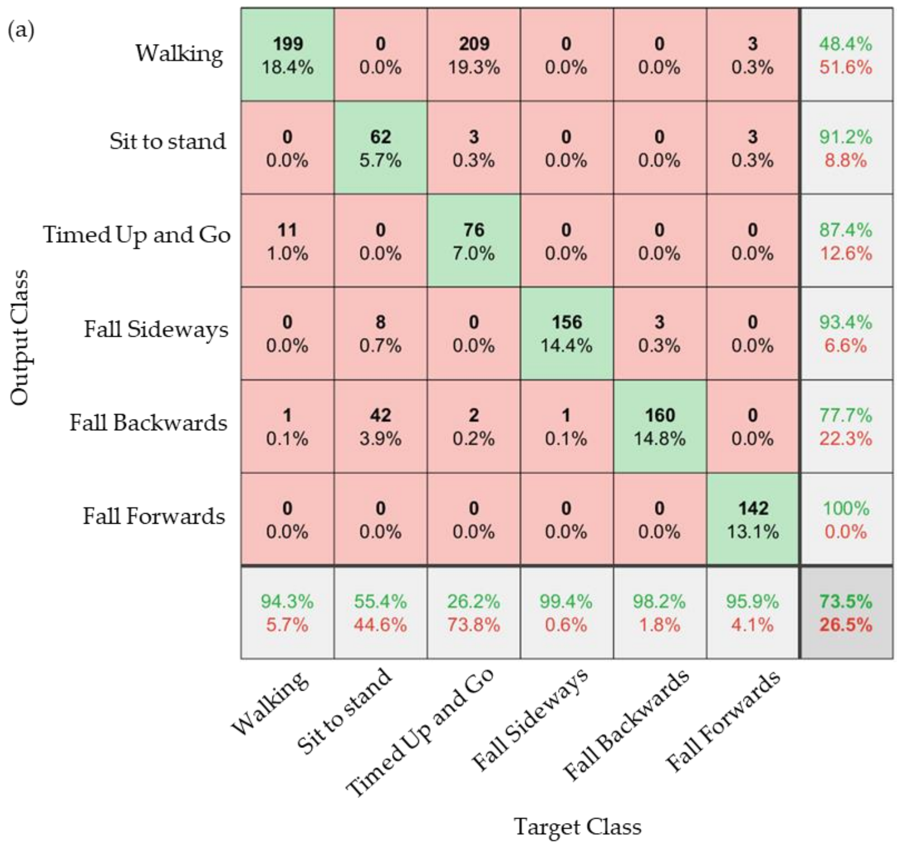
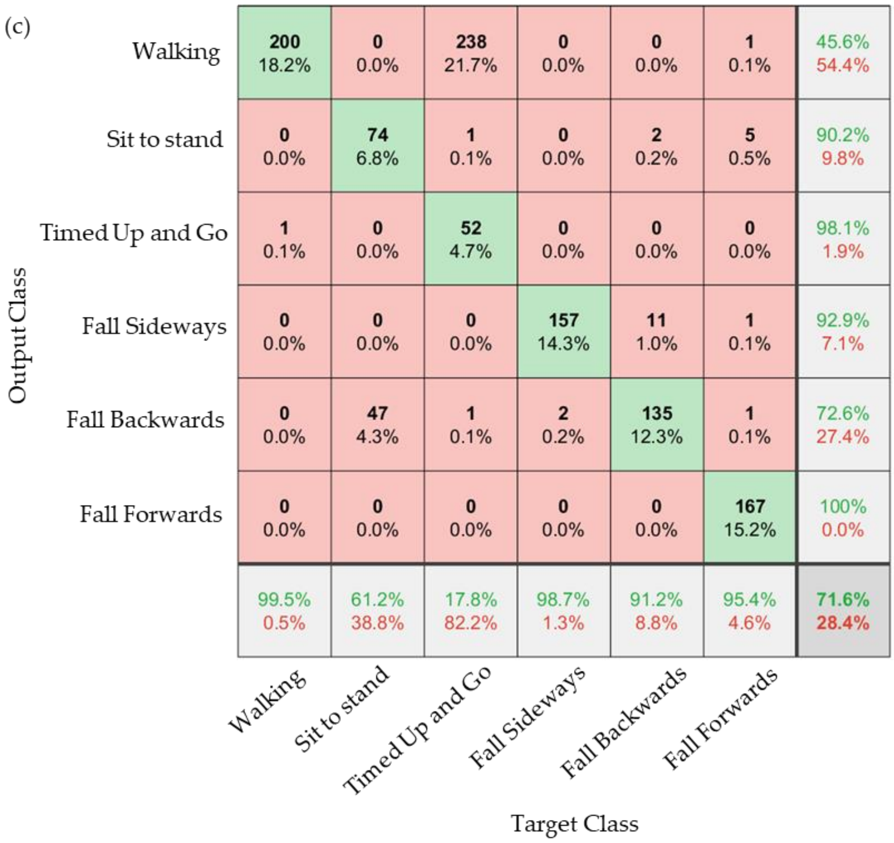


Figure 5.20 Confusion matrices for the data taken from the right foot. (a) Acceleration data. (b) Angular velocity data. (c) Both acceleration and angular velocity data. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

Figure 5.20 shows that using the angular velocity data on its own allowed for a more accurate classification when compared to using the acceleration data on its own. The sit to stand for all three conditions (as shown in Figure 5.20 a, b and c) was 100% accurate. Like in Figure 5.18, the walking and 'Timed Up and Go' could sometimes be misclassified. This was because these activities are similar, and the majority of the 'Timed Up and Go' test consisted of walking and turning, which was also the case for the walking activity. In Figure 5.20a, it was seen that the acceleration data misidentified walking as the 'Timed Up and Go' activity in a significant number of cases, with walking only being correctly identified in 47.7 % of cases. However, as previously mentioned it only mattered that the algorithm could identity between falls and non-fall activities (ADLs). The classification of falls accurately (particularly the forward fall) was observed to be best when using either the acceleration data or a combination of the acceleration data with angular velocity data.





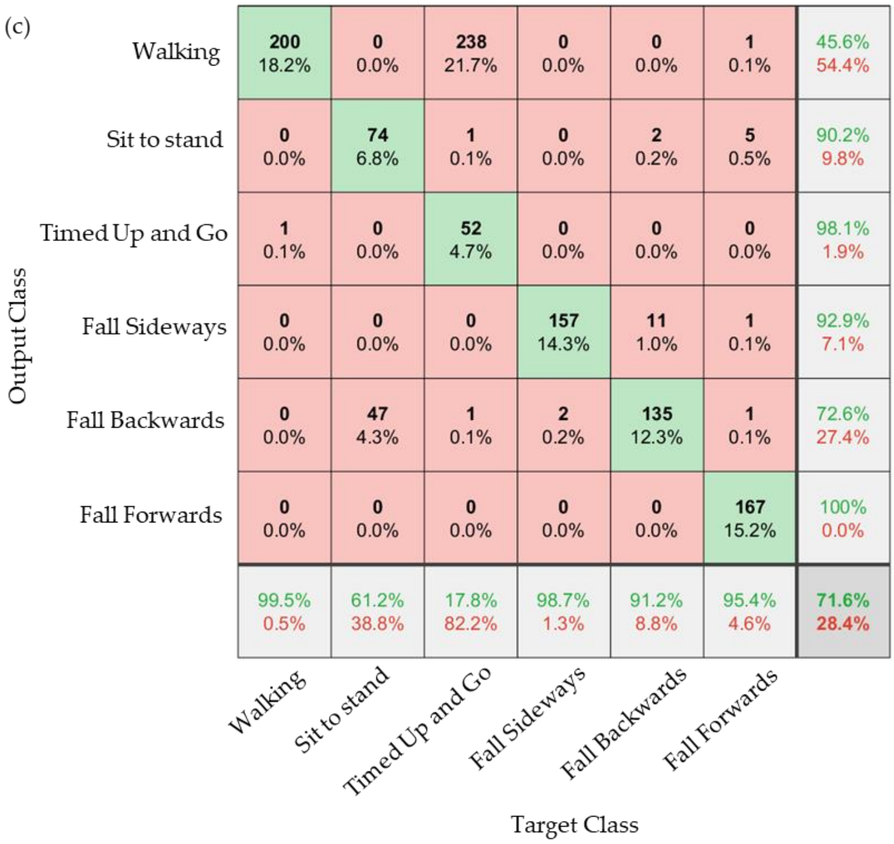


Figure 5.21 Confusion matrices for the data taken from the left foot. (a) Acceleration data. (b) Angular velocity data. (c) Both acceleration and angular velocity data.

Figure 5.21 shows, like Figure 5.19 and Figure 5.20, using the angular velocity data alone allowed for a more accurate classification when compared to using the acceleration data alone. Unlike, the right foot, the sit to stand was only 100% accurate when using the angular velocity data. Like in Figure 5.18 and Figure 5.20, the walking and 'Timed Up and Go' could sometimes be misclassified, which has been discussed above. However, it was much more prevalent when looking at the left foot data on its own.

The table below compared the nine different iterations of the confusion matrices, exploring using data from the left, right or both feet and against combined (accelerometer and angular velocity) or individual measurements form the motion sensing E-yarn. These percentages are taken from confusion matrices in Figure 5.18 – Figure 5.23.

Table 5.7 Overall accuracy of the acceleration, angular velocity and both combined on each foot individually and both together. Values have been taken from the confusion matrices. Taken from [1]; this table is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

	Right Foot	Left Foot	Right and Left Foot
Acceleration data	72.1 %	73.5 %	73.2 %
Angular velocity data	85.4 %	87.9 %	83.9 %
Combined acceleration and angular velocity	85.7 %	71.6 %	81.2 %

The table showed that generally models trained using the angular velocity data were more accurate in classifying activities than when trained using the acceleration data. For the left foot, the confusion matrices showed that the acceleration data was more accurate for sideways falls, this was because all of the participants fell on their right side. Therefore, the right foot did not move as much as the left foot (observed in the videos of the activities). The use of the angular velocity data was generally better for the identification of falls. The left foot angular velocity data provided the most accurate classifications (87.9 %) followed by the right foot combined acceleration and angular velocity data (85.7%). A key finding was that the use of data from one foot to train the algorithm often provided a more accurate classification than when the data from both feet where used. It should be noted that the confusion matrices used to create Table 5.7 all showed the same misidentification between the walking and 'Timed Up and Go' activities observed in Figure 5.17 - Figure 5.21.

While different activities could be identified with a high accuracy, for this device the identification of specific activities was not necessary, and instead only when the wearer was conducting an ADL or had fallen was really of interest. Figure 5.22 shows the confusion matrix that classifies between the ADLs (non-falls) and falls. The results show a high accuracy of 96.1%. This result proved that the over-sock could be used to accurately detect falls.

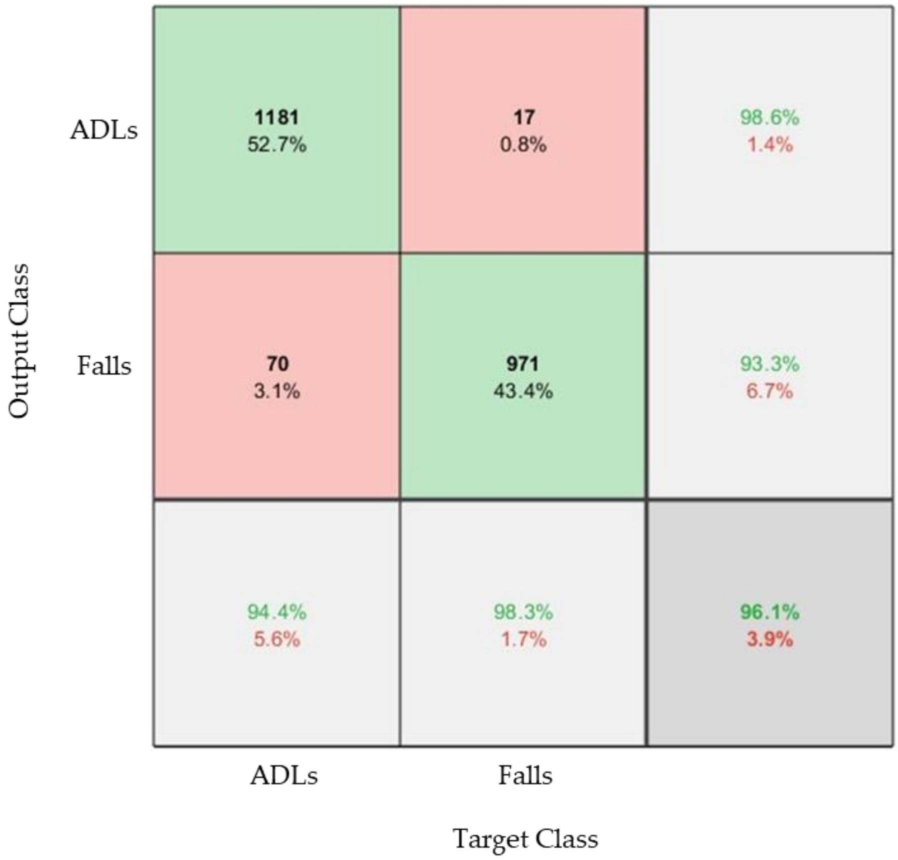


Figure 5.22 Confusion matrix that classifies between the three types of ADL (walking, sit to stand, 'Timed Up and Go') and the three types of fall. The model was trained and tested using datasets from both feet and both the acceleration and angular velocity data. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

Previously it was observed that taking measurements from only one foot improved the accuracy of the model. By taking data from only the right foot (informed by Figure 5.20 and Table 5.7) the model was re-trained and the following confusion matrix was achieved (Figure 5.23).

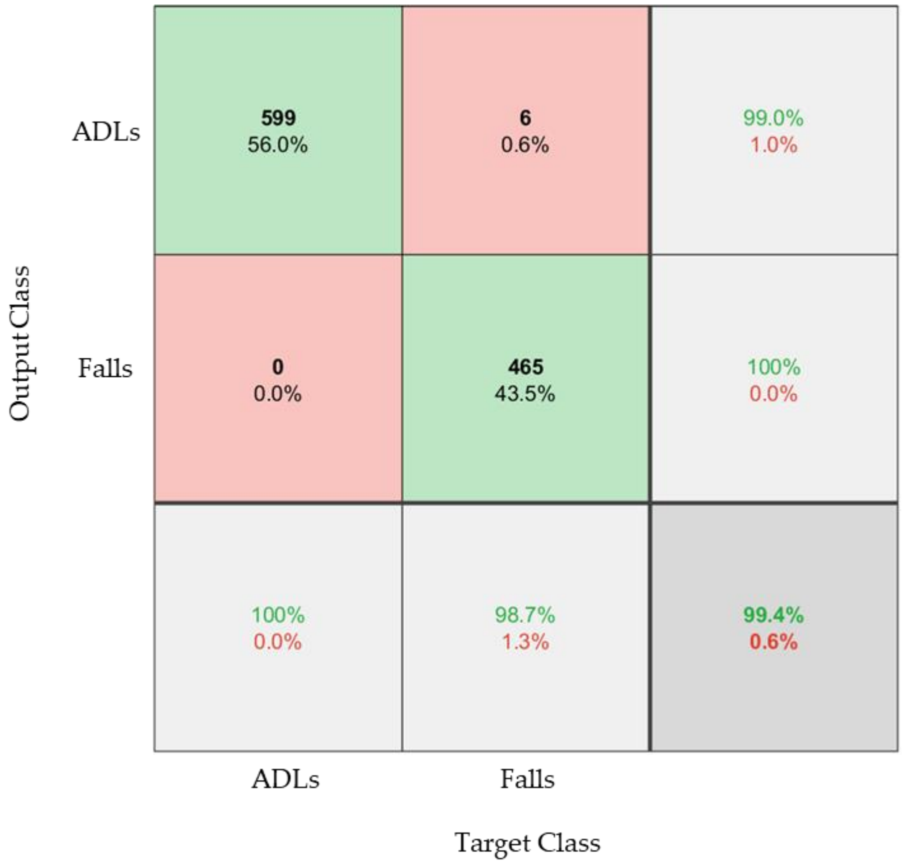


Figure 5.23 Confusion matrix that classifies between the three types of ADL (walking, sit to stand, 'Timed Up and Go') and the three types of fall. The model was trained and tested using datasets from only the right foot and both acceleration and angular velocity data. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

An accuracy of 99.4 % was achieved. Not only does this further evidence the suitability of the over-sock and algorithm for detecting falls, but it showed that only one over-sock was sufficient. This is important for the implementation of such as system as one over-sock is significantly less costly than two.

5.5.3 Controlled Stumble Data

The graphs presented below show the data from the controlled stumble activity for participants 3 and 11. This was the only activity where the patterns in the data were not visually observed to be consistent between participants. Data from Participant 3 (Figure 5.24) and Participant 11 (Figure 5.25) are presented as they performed the stumble in two different ways.

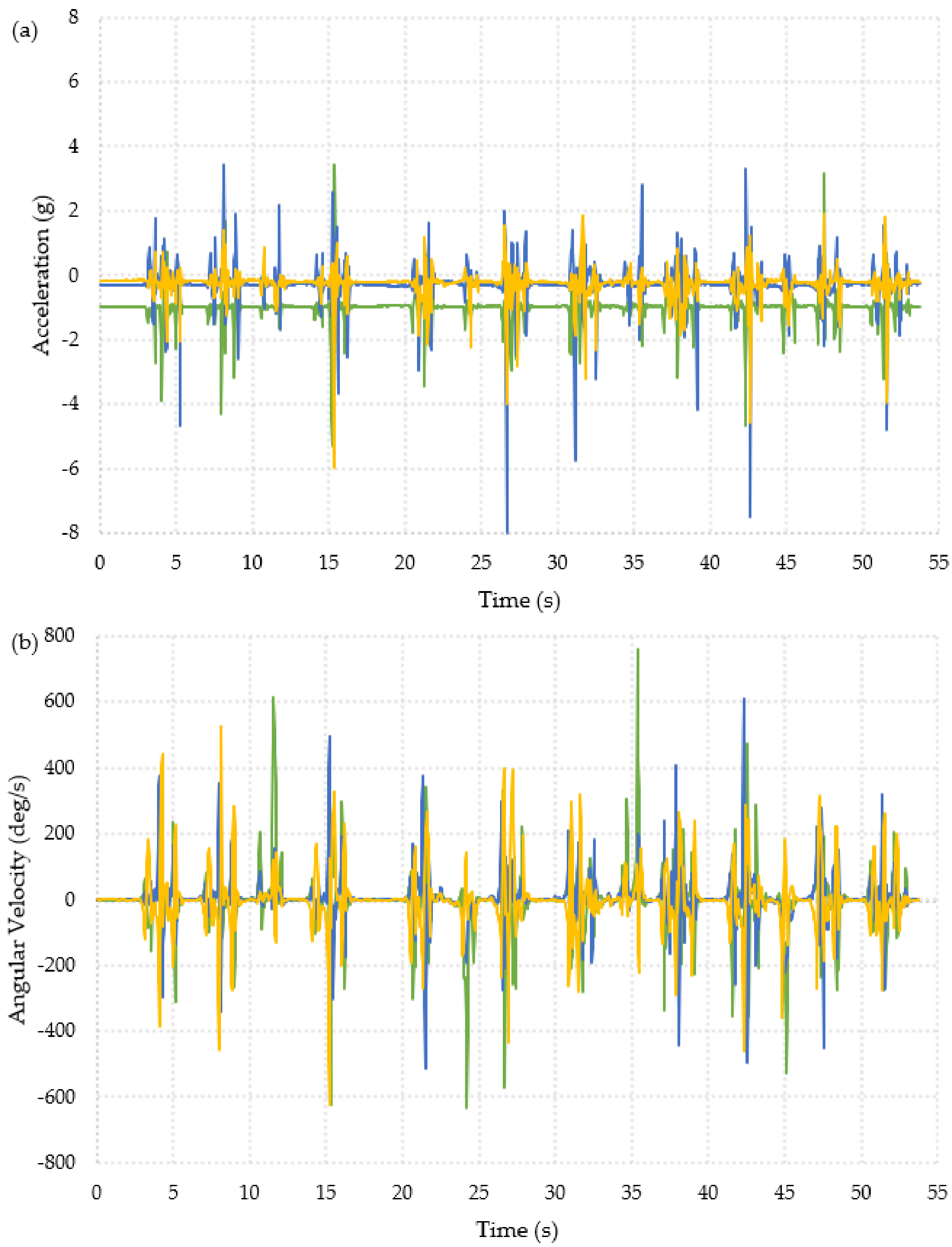


Figure 5.24 Graphical representation of the data collected from one foot for Participant 3 during the controlled stumble activity. X-axis = , y-axis = , z-axis = . Ten repeated stumbles are shown. (a) Acceleration. (b) Angular velocity. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

Figure 5.24 shows data for when Participant 3 was stumbling. This participant took a step to stumble and then paused before performing the next stumble. This participant stumbled ten times and turned four times during the activity. The turns can clearly be seen in Figure 5.24b; when the participant turned there was either a large increase or decrease in the x-axis angular velocity, seen at 12s, 24s, 35s and 45s. This change was much less obvious in the acceleration data.

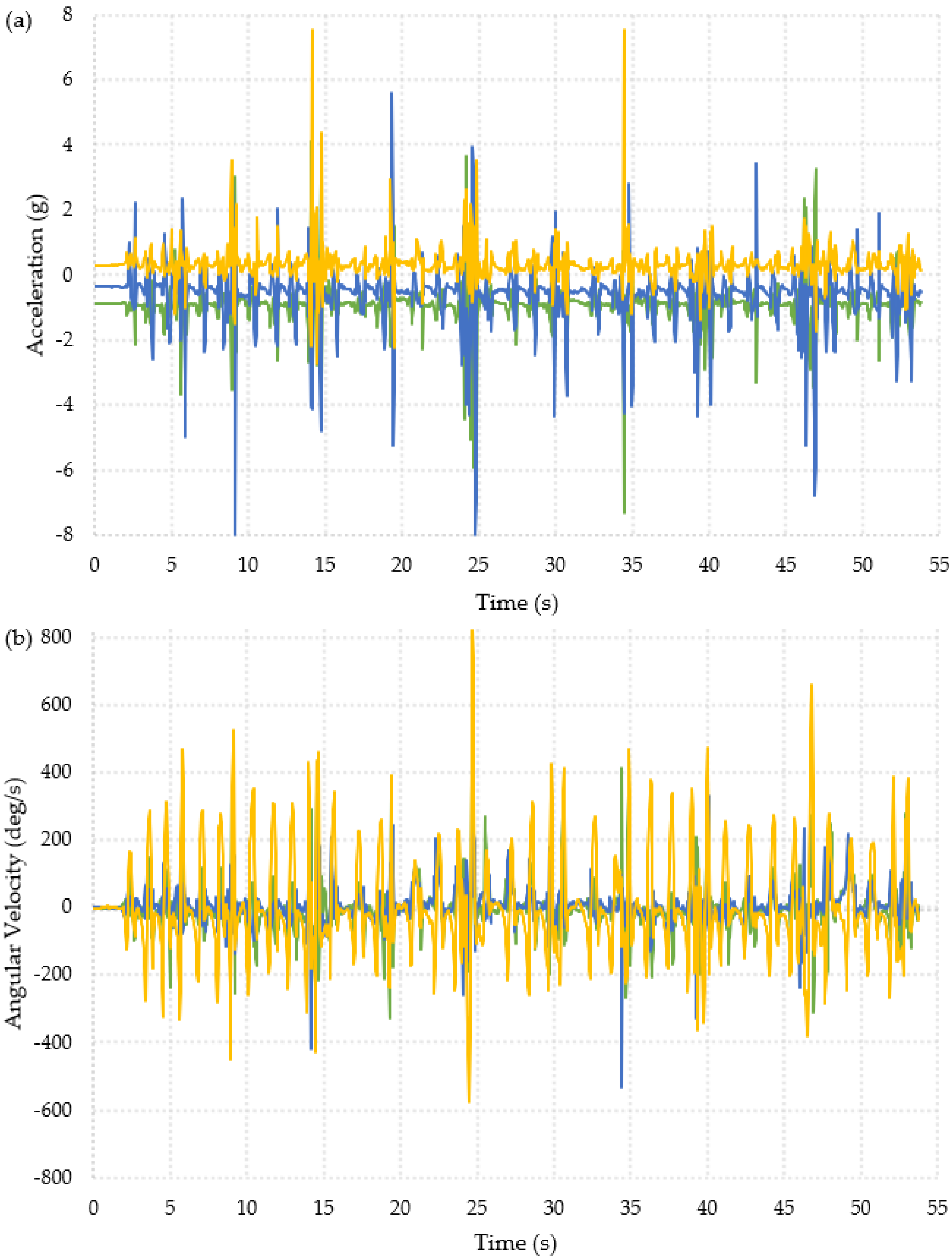


Figure 5.25 Graphical representation of the data collected from one foot for Participant 11 during the controlled stumble activity. X-axis = ——, y-axis = ——, z-axis = ——. Ten repeated stumbles are shown. (a) Acceleration. (b) Angular velocity. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

Figure 5.25 shows the acceleration and angular velocity data recorded for Participant 11 during the stumbling activity. This participant interpreted the activity differently compared to Participant 3. They continuously walked around the room and completed the ten stumble repeats in that time. Figure 5.25a shows the acceleration data, and there are large changes in acceleration in the y-axis corresponding to each stumble. The limit of the sensor was set at ±8g, which the participant exceeded twice. There were also visible changes in the z-axis for each stumble, but these tended to not be as large as the changes in acceleration in the y-axis. The angular velocity data seen in Figure 5.25b showed large changes in the z-axis that are larger than those seen during the walking activity and the acceleration change for the stumble was larger than for falling. This suggested that a threshold value for a fall when the sensor is place on the ankle would produce false positives if a person stumbled.

While the type of stumbles conducted by the participants were highly varied, the very high accuracy of the system when comparing fall events and ADLs meant that extracting abnormal events (stumbles) might be possible. This could represent a near-fall in a practical scenario. As the right foot gave the best results (when all data was used) the model was retrained using three output classes: ADL, fall, stumble (Figure 5.26). It should be noted that these datasets were not balanced as there were significantly less stumble events on which to train the model.

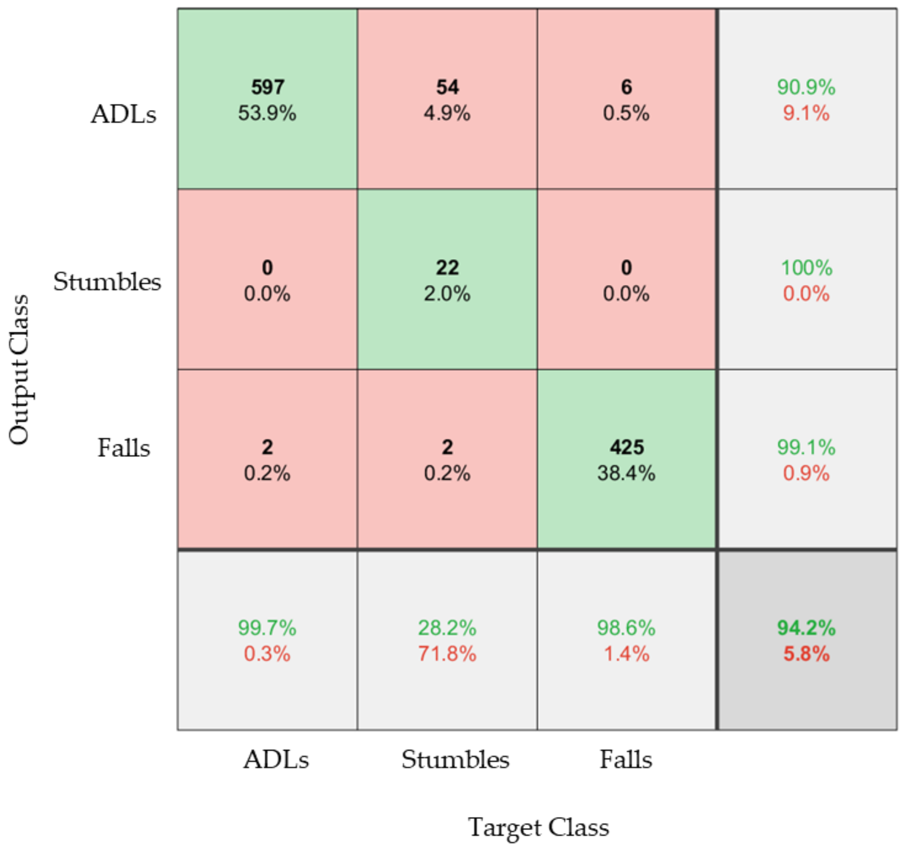


Figure 5.26 Confusion matrix that classifies between the three types of ADL (walking, sit to stand, 'Timed Up and Go'), the three types of fall, and a near-fall event (stumble). The model was trained and tested using datasets from only the right foot and both acceleration and angular velocity data. Taken from [1]; this image is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).

Figure 5.26 clearly showed that stumbles could be identified, distinct to both falls, and ADLs, with a 94.2 % accuracy. This showed that the sock can detect near fall events. Future work will need to repeat these experiments with a greater number of stumbles and near-fall activities to further validate the accuracy of the proposed system.

5.5.4 Feedback on Sock Design

Specific design decisions were made to ensure that the over-sock was both functional and user-friendly. The sock was designed to be comfortable and therefore cushioning for the E-yarn and hardware was integrated into the knit design (by knitting a spacer structure). Additionally, the opening to the pocket that contained the hardware module was left relativity large for ease of access during the trials, but also as older women are more likely to develop osteoarthritis [25] and rheumatoid arthritis than men [26], potentially making handling the hardware difficult for them. During the human trial, participants were given the option to provide feedback on the comfort of the sock. The participants found the over-socks comfortable during the trial. Two of the participants initially wore the over-sock inside out and could not feel the hardware. Another participant wore the over-sock upside down and did not notice any discomfort. This implies that it would be best to add direction on the sock to indicate which way to put it on. One participant mentioned that they liked the over-sock as the electronics were unnoticeable.

5.6 CONCLUSIONS

This work presents an over-sock with an embedded IMU that can be used for fall and near-fall detection. By implementing a Bi-LSTM, three different ADLs and three different falls could be differentiated with an accuracy of 85.7 %, ADLs and falls could be distinguished with a 99.4 % accuracy, and ADLs, falls, and stumbles (near-falls) classified with a 94.2 % accuracy. The work established that the identification of different activities was more successful when only data from one foot was used instead of both. From the results it is proposed that a monitoring solution of this type be worn on the right foot.

Future work will include repeating the study with additional stumbles, as this dataset was not balanced with the ADLs and falls for this study. Further, with the utility of the device proven it will be important to test the over-sock on older people, as opposed to the young healthy volunteers used in this study, as peoples gait patterns are known to change with age. Repeating the study with a male cohort and validating the system for fall and near-fall detection with men will also be part of future work. Ultimately the proposed over-sock could be a powerful tool in helping understand if older adults are at risk of falling.

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CHAPTER 6. DISUSSION

6.1 INTRODUCTION

This chapter contains an analytical discussion of the design and development of the final electronic textile (E-textile) prototype. Some of the discussion was also included within the relevant chapters and has been summarised here.

The literature review in Chapter 2 identified the following key gaps in the literature, for fall and near-fall detection, are sensor placement along with the sampling rate and sensor itself required. In the field of E-textiles, the use of human-centred design HCD is uncommon and there are currently no inertial measurement unit (IMU) electronic yarns (E-yarns), or IMU E-textiles. Finally, there are no E-textile fall or near-fall detection garments that have been developed. Furthermore, this thesis has used an HCD approach to design the fall and near-fall detection garment.

Section 6.2 addresses the gap in fall and near-fall detection studies and examines the method developed to test the prototype, using the literature presented in Chapter 2 and the pilot study presented in Chapter 3. Section 6.3 analyses the electronic and garment design of the E-textile prototype. The garment was designed using a human-centred design (HCD) approach and this influenced the design of the electronics, as discussed later. The electronic design includes the research that was conducted to develop the electronic yarn (E-yarn) and the supporting hardware needed to make the over-sock function.

6.2 TESTING OF THE PROTOTYPE

6.2.1 SENSOR CHOICE

The sensor chosen for the thesis was an inertial measurement unit (IMU). This is a combination of an accelerometer and a gyroscope. The review of the literature in Chapter 2 showed that the IMU is most commonly used for near-fall detection [1–5] and an accelerometer is most commonly used in fall detection studies [6,7]. This is discussed in Chapter 2. The advantage of an IMU over a separate accelerometer and gyroscope is that only one electronic yarn was made, rather than two. In addition, it was chosen to determine if both data types are required. The pilot study concluded that accelerometer data alone was sufficient for the detection of falls but that having both the accelerometer and gyroscope data would be beneficial in classifying between activities. The human trials used the machine learning algorithm to examine the different combinations of accelerometer and gyroscope data. The results shown in Table 5.7 showed that the gyroscope data alone might be sufficient to classify between falls and activities of daily living (ADLs). Ultimately, using both was determined to be the most accurate for near-fall detection.

6.2.2 Pilot Study

Within the literature, each study used different sensor placement, sampling rates and activities. Therefore, the pilot study presented in Chapter 3 was devised to develop a method for further studies by determining an optimal location for the sensor or sensors, if both accelerometer and gyroscope data are required (discussed above), the sampling rate and the minimum number of activities for the participants to perform. In addition, it could be used as a method for other researchers to follow. The placements chosen for the study were wrist, chest, waist, lower back, thigh and ankle. The sampling rates tested were 25 Hz, 50 Hz and 100 Hz. The placements and sampling rates were chosen based on the literature that is presented in Table 2.2 and Table 2.3. The activities chosen were walking, kneeling, sitting on a chair and stool, lying down, reaching high and low, 'Timed Up and Go' tests (standing from seated, walking and returning to seated), 'Turn 180°' and falling onto a crash mat. Walking, sitting down on a chair and stool, kneeling, lying down and reaching high and low were used as they are tasks that mimic ADLs. The ability to perform ADLs is essential for independent living [8]. The 'Timed Up and Go' and 'Turn 180°' tests were chosen as they were used for fall risk assessment by clinicians [9]. In addition, the activities chosen were commonly used in fall detection studies that were presented in Table 2.2.

A commercial motion tracker (MetaTracker) was used for this study. This was chosen as the tracker contained an IMU and had an associated software to collect the data. The data was visually analysed as the MetaTracker did not collect the data with a consistent sampling rate. In addition, fall detection studies within the literature tend to analyse data using some form of algorithm, whether that be a basic threshold or machine learning [10–20]. As a result, the purpose of this study was never to develop a machine learning algorithm but to truly understand what the data was showing.

It was found that multiple places could be used for the accurate detection of a fall, which has never been fully explored in the literature. However, the results showed that the wrist, which is a common placement for commercial fall detection products, is the least accurate location. For fall detection the most accurate placements included the thigh, ankle and waist. The ADLs and falls could be classified by using the accelerometer data alone, but it was beneficial to have the gyroscope data to classify between each activity. The study also tested various sampling rates and it was found that 25Hz was the most efficient. This is because the higher sampling rates collected too much information and created confusion when trying to visually analyse the data.

This study was needed as, to the knowledge of the author, no other study within the literature has shown a complete dataset that very clearly shows the data and compares various sampling rates and different placements on the body. This work will be useful for other researchers as a research method to use for other sensors or other trials. In addition, the data has been shared on a repository to allow other researchers to access the data and contribute to fall detection datasets [21].

6.2.3 HUMAN TRIAL

The results from the pilot study directly affected the method used in the human trial that tested the final prototype. The final prototype chosen was the over-sock based on the HCD project presented in Chapter 4 and discussed in Section 6.3. The over-sock prototype contained the IMU at the ankle. The participants were asked to perform the following activities: walking with a turn, sit-to-stand from a chair, 'Timed Up and Go', a controlled stumble, and three types of falls onto a crash mat fall (sideways, backwards, and frontwards). These were chosen based on the results of the pilot study. The pilot study showed that sitting on a chair and stool, as well as the kneeling activity, gave similar patterns, both of the walking activities were not needed and the walking activity showed a turn, therefore a separate turn was not required. The controlled stumble was used to mimic a near-fall and the three types of falls were needed as people do fall in all directions. Each participant performed the controlled stumble however they felt was appropriate.

The data was analysed visually and using a machine learning algorithm. The raw data has been added to a data repository [22] to ensure transparency, allow other researchers to use the data and contribute to fall and near-fall detection datasets. The machine learning analysis was conducted by an expert computer scientist, with experience in using an algorithm (Bi-directional long term short-term memory network) that can classify time series data with relation to gait and movement and has previously been successfully used [23–25]. This was necessary as the Advanced Textile Research Group (ATRG) do not have this type of expertise and it highlights the importance of collaboration to conduct the best research possible.

The human trial found that three different ADLs and three different falls could be differentiated with 85.7% accuracy, ADLs and falls could be distinguished with 99.4% accuracy, and ADLs, falls, and near-falls could be classified with 94.2% accuracy. The trial also found that using data from one foot was more successful than using data from both feet for identifying different activities.

6.2.4 LIMITATIONS

The limitations of both the pilot study and the human trial are that the participants were young healthy female volunteers. Females were chosen as older women have more non-fatal falls than older men. As this research was used as a proof-of-concept, it was unethical to ask older women to perform the near-fall and fall activities.

A limitation of the pilot study was the number of participants that were utilised in the study, The restriction was in place as the study was conducted during the COVID-19 pandemic. A limitation of the human trial is that the number of types of near-falls was not balanced between the ADLs and the falls. Another limitation of the human trial was that although the results showed that data from one foot was more efficient than both feet, the participants were not asked if they were right or left-footed. As right-footedness is more dominant than left-footedness [26], this needs to be studied further.

6.2.5 SUMMARY

The pilot study addressed the variations in sensor placement and sampling rate found in the literature. It determined optimal sensor placements (thigh, ankle, waist) and an efficient sampling rate (25Hz) for fall detection. The study filled knowledge gaps by showcasing a comprehensive dataset comparing various placements and sampling rates. This dataset can serve as a research method for future studies and is available for other researchers to access, enhancing collaboration in the field.

The results of the pilot study directly influenced the human trial, which tested the final prototype. Activities for the human trial were selected based on pilot study findings. The trial demonstrated high accuracy in distinguishing between ADLs, falls, and near-falls. The trial also showcased the importance of collaboration between different disciplines.

The implications of this work extend to the development of more accurate fall and near-fall detection systems and datasets for future research. In addition, the IMU E-yarn can be used in other motion-related studies for example gait. This work also showcased the importance of collaboration to utilise other disciplines' expertise to ensure the research is of the highest quality.

6.3 Designing the Prototype

There were two components of research required to design the final functioning prototypes. One component included the work presented in Chapter 4, which looks at what women aged 65 and above would be willing to wear to detect near-falls and falls. The second component included the work presented in Chapter 5, specifically the E-yarn (Section 5.2) and hardware (Section 5.3) development.

6.3.1 Garment Design

The study presented in Chapter 4 aimed to design E-textile garments that older women were willing to wear, specifically for fall and near-fall detection. A human-centred design approach was used to develop a garment. For this research, semi-structured interviews were conducted to allow a multidisciplinary team to create prototypes based on their answers and the three placements determined in the pilot study (thigh, waist, ankle). Subsequently, these were showcased at an in-person focus group with five older women to feel and give feedback.

An HCD approach was chosen as the purpose of the study was to explore the needs and wants of the intended users, with an idea of where the garment needed to be and how it functions. From the interviews it was clear that the older women were not familiar with E-textiles, meaning they could not imagine what they might look and feel like. Therefore, it was important to allow the multidisciplinary team the freedom to design and create based on the analysis of the interviews rather than using co-design.

The need to use HCD to design an E-textile has been discussed within the field [27,28]. However, in practice, the study that is closest to achieving this type of research is MATUROLIFE [29]. The key difference between the study presented in Chapter 4 and MATUROLIFE is that MATOURLIFE used co-design as its methodology and was completed on a much larger scale (included nine countries). Within the fall and near-fall detection field, to the knowledge of the author, there have been no studies on the design of the device, with the focus being on the machine learning algorithm and accuracy.

This project showed the importance of multidisciplinary collaboration. Usually, the designers and the technologists (scientists/engineers) do not work together. They tend to concentrate on their own discipline. In this study, there is collaboration between the technologists and designers. The expertise used in the prototype development team included E-textile development, E-textile design, textile and fashion design, seamless knit manufacturing, and pattern cutting. Each expert was allowed to make decisions based on their knowledge. For example, the choice of fabric was left to the expert making the garment prototype. The placement of the sensor was determined by the E-textile technology development. There was collaboration in decisions of where the hardware module should be placed and how it was incorporated into the design. The prototype development phase showed that no one person contains all the expertise required to develop this type of technology. In addition, the ability to discuss and collaborate without ego is necessary for successful outcomes.

The results of this study showed that there is a reluctance to accept this type of technology, as although the women were 65+, they still did not perceive themselves as old enough to require it. However, there was also resignation in knowing that it would be needed at some point. This is in agreement with studies on technology acceptance [30], however, there are no real academic studies that explicitly discuss how older adults feel about falls and imbalances. Older adults do not want to be made to feel old nor do they want to stand out or showcase any vulnerability. This needs to be explored further and ties into the best way to market devices aimed at healthy ageing more generally. People do know what is good for them but tend to ignore it anyway.

When discussing E-textiles, there were concerns that seamless integration of the technology would be expensive, require them to own multiple and limit their clothing options. In addition, when discussing clothing preferences, the most important term used was comfort. In this case, this meant physical comfort, which usually required stretch in the garment, as well as emotional comfort, i.e., age-appropriate, loose fitting and flattering. This aligns with other research into the complexities of design for older women [31,32]. There is limited research into how older adults feel about E-textiles when discussing the quality of the technology and textiles. Key concerns are durability, replacement frequency, associated costs, and the necessity of owning multiple E-textile items. Further investigation in these areas is needed to better understand older adults' attitudes and preferences toward E-textiles, and healthy ageing more generally. In addition, it would be useful to collaborate with healthcare professionals to discuss their opinions on aiding healthy ageing.

To combat the views of older women found in the interviews, this study focused on designing garments that are worn regularly (socks) or under clothing (shorts) and attachable to clothing (a patch). The prototypes were presented to five older women during a face-to-face focus group and the sock was chosen as the final prototype. It is important to note that the participants in the focus group were willing to wear each of the prototypes for different reasons, dependent on the weather, and changes to the colours and designs. However, there was a misunderstanding on the use of the patch prototype. The participants did not seem to understand that the patch could not be placed anywhere on the body. The sock was chosen as it was ranked second in the more detailed questionnaire. The results are shown in Table 4.1.

6.3.2 E-Yarn and Hardware Development

The E-yarn and hardware development sections presented in Chapter 5 show the difficulty of creating an IMU E-yarn. This was the first IMU E-yarn that had been developed and it was difficult for a variety of reasons. The first was the number of solder pads that needed to be connected (ten) along with the size of the solder pad (0.25mm x 0.35mm). Previously E-yarns with a maximum of five connections have been made [24]. Additional challenges included designing and connecting an operating circuit printed circuit board (PCB) that was as small as possible to ensure that the IMU functioned correctly. The operation circuit PCB that was developed was 1.5cm x 1.5cm and contained a connector to ensure that the IMU E-yarn could be disconnected from the hardware and operating circuit.

Originally, only seven solder pads were used for the IMU E-yarn, however during the testing process it was discovered that the other three pads were required. Furthermore, the IMU used for the E-yarn was chosen due to availability issues that were created by COVID-19 (discussed in Chapters 1 and 5). It was the smallest IMU available at the time (4mm x 4mm x 0.9mm). As this IMU was relatively flat, it was encapsulated in the same shape rather than being made into a pod as has previously been done. The flat shape allowed the final E-yarn to be hidden in the over-sock and undetectable when worn. Having successfully created the IMU E-yarn, the wider implications are that there is potential to create E-textiles that are fully comprised of E-yarns.

Currently, the hardware module used in the over-sock is rigid and made of commercially available components. The hardware module includes the microcontroller, the operating

PCB and the connector and was designed to be as small as possible. The hardware module was developed using the feedback from the interviews and focus group. The connector allows the hardware module to be removed for washing and to allow it to be connected to other garments. Another consideration of the design of the hardware module is that although it needs to be compact to reduce its visibility, it needs to be easy to use. Within the focus group, the simulated hardware was too small and fiddly for the women. As women are more likely to develop arthritis as they age [33], it is significant for the design of all hardware.

6.3.3 Limitations

Due to the COVID-19 pandemic, it was difficult to recruit older women for the interviews and focus group. Originally, the plan was to contact Age UK to gain access to a larger number of participants, but this was not possible during the timeframe of the project. It was easier to recruit participants for the interviews as these were conducted online, however, only one focus group was possible. It would have been beneficial to have multiple focus groups to continue to refine the design of the prototypes. This would be more have been more in line with the MATUROLIFE project [34]. The biggest limitation of the E-yarn and hardware development was access to the materials, which has been discussed in Chapter 5 in more depth.

6.3.4 Summary

The HCD study has given new information into the insights of older women with regard to falls, healthy ageing, technology and E-textiles. It has also shown the need for multidisciplinary research to ensure that the final prototype was functional but also would be worn by the intended users (older women). The work can be extended into wearables more generally as well as how best to assist healthy ageing.

The E-yarn and hardware development was challenging but also considered the preferences of the intended users. The IMU has been the most complex component that has been successfully turned into an E-yarn. The wider implications are that there is E-textiles will be comprised completely of E-yarns, with no rigid hardware modules.

6.4 Conclusions

This chapter has shown the importance of collaboration to ensure that the research being undertaken is of the best quality. Collaboration has been key to the success of this thesis as it has allowed different experts to come together to share knowledge. It ensured that the final prototype was comfortable and aesthetically pleasing. Furthermore, it has allowed the use of machine learning to determine the accuracy of the final prototype.

The pilot study and human trial can be used by other researchers as a method to follow when developing a fall detection or near-fall detection device. The data from both studies is openly available to allow other researchers to analyse and compare.

The HCD approach was crucial because it gave insight into the intended users of the technology. The use of HCD is fairly limited in the E-textiles field and has not been seen in the fall/near-fall detection field. The final prototype is a good compromise between the needs of the users and the technical challenges of E-textile development. The development of an IMU E-yarn is significant as it is the first known IMU E-yarn. In addition. This is the first IMU that has been integrated into a textile and the first fall and/or near-fall detecting textile.

Chapter 7 focuses on the conclusion, including contributions to knowledge and future work.

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CHAPTER 7. CONCLUSION

7.1 CONCLUSIONS

The work presented in this thesis achieved the goal of designing and developing an electronic textile garment for fall and near-fall detection, that people are willing to wear. Looking back at the original aims and objectives of this thesis, all of the research questions have been answered.

RQ1: What are the most appropriate sensors or combination of sensors for the accurate detection of near-falls?

The sensor selection was made after reviewing the literature on fall and near-fall detection studies, discussed in Chapter 2. The sensor used was an inertial measurement unit (IMU). A six-axis IMU measures both acceleration and angular velocity. Nine-axis IMUs contain the addition of a magnetometer, which was not found to be used often in fall and near-fall detection. Measuring acceleration is the most common method for fall detection in the literature. In addition, a lot of studies have added angular velocity measurements to give more accuracy. In near-fall detection studies, the IMU is used almost exclusively. In most cases the placement of the sensor within the literature varied significantly, without any apparent reason given. Most often these included the waist, chest, wrist, lower back, thigh, and ankle.

RQ2: Where is the most appropriate placement for the sensor(s) on the body?

The pilot study presented in Chapter 3 used commercial motion trackers each containing an IMU, placed on six positions on the body that were informed by the literature. This study required the young healthy volunteers to wear the six motion trackers simultaneously which measured the acceleration and angular velocity changes of their body as they performed various activities. These activities included activities of daily living (ADLs) and a sideways fall onto a crash mat. In addition, various sampling frequencies were tested as this parameter is not defined within the literature. The study showed that the sensor should be placed on the lower body, that is the waist, thigh or ankle and the sampling rate chosen was 25 Hz. The relatively low sampling rate of 25 Hz allowed for fast processing times. Furthermore, the higher sampling rates did not show any added benefits.

RQ3: How to design an E-textile garment that older people are willing to wear for fall and near-fall detection?

Chapter 4 aimed to understand user needs for fall or near-fall-detecting E-textile garments and explored the suitability of different designs. It must be noted that this thesis has focused on creating an E-textile garment for women, as they are more likely to fall than men [1]. In addition, women tend to be discounted when wearable technology is designed as gender-neutral [2]. Initially, interviews were held to explore clothing preferences, attitudes to technology, including wearable technology and health monitoring devices, as well as attitudes towards falls and wearable devices for fall and near-fall detection. Following these interviews, three non-functional prototypes were developed by an interdisciplinary team including experts in E-textiles, textiles and design. These prototypes were shared with a small focus group to receive feedback and to decide on the final E-textile garment design. The prototypes were designed by the information found from the pilot study (presented in Chapter 3), which was that the best placement for a sensor was either the waist, thigh, or ankle.

Both the interviews and focus group showed that designing for older women is complex and it is challenging to please everyone. Therefore, when designing an optional E-textile garment (a device not prescribed as a required medical wearable), it was easiest to make a form of accessory or under layers that do not interfere with the user's normal clothing. This was confirmed by the preferred prototype being an attachable patch. However, the participants misunderstood the use of the patch and wanted to add it to wherever they felt would be most comfortable, rather than accept it being located/placed in a strict position. Moreover, the user group felt that it would be preferable to have different designs of fall-detecting garments to be used during different activities.

In addition to the difficulties of designing a garment and having it adopted, the interviews and focus group showed that the participants felt that there was a stigma associated with getting older that was difficult to overcome. The idea of wearing any form of technology for fall prevention from the age of 65 made them feel old. Although the women knew they were old, they still did not view themselves as old or frail enough to need this type of technology.

There was a resignation to the fact that one day they would need it. They would wear a monitoring device if they were told to by a healthcare professional rather than by choice.

RQ4: Does the final E-textile garment function as designed?

The final E-textile garment design selected was the over-sock. An IMU was used to create an electronic yarn (E-yarn) that was inserted into the over-sock. The E-yarn was tested at each stage of manufacturing (soldered, encapsulated and braided). This ensured that the unusual soldering technique, encapsulation and different covering materials did not affect the fundamental behaviour of the IMU. A detailed study with human participants, informed by the pilot study, was then conducted using the over-sock. The study involved young healthy volunteers wearing an over-sock on each foot performing three types of ADLs, a simulated near-fall, and three types of falls onto a crash mat. The simulation of the near-fall was a controlled stumble with each participant conducting their version of a controlled stumble very differently. Data from the study was used to train a machine learning algorithm that was then tested using further datasets. The results showed that six different types of activities (the three types of ADLs and the three types of falls) were classified with an accuracy of 85.7%. When only distinguishing between the ADLs and falls, the accuracy of detection was increased to 99.4%. In addition, when classifying between the ADLs, the falls, and the near-fall event (controlled stumble) the accuracy of detection was 94.2%.

7.2 Contribution to Knowledge

This thesis has contributed new knowledge in the field of E-textiles, wearables, healthy ageing, design and, fall and near-fall detection in the following ways:

- Explicitly determining that the most appropriate sensor for monitoring near-fall detection is an IMU (*fall and near-fall detection*).
- Finding that the optimal placement of an IMU for a wearable fall and/or near-fall detection device is on the lower body and that the wrist is not an acceptable placement (*fall and near-fall detection*).
- Developing a research method for others to follow when trying to determine different sensor placements and experimental parameters (*fall and near-fall detection, wearables and E-textiles*).

- Fabricating the first IMU E-yarn, which has successfully been incorporated into an E-textile garment for fall and near-fall detection. With the wider implication that E-yarn technology can be used for more complex sensors, and that can be applied to developing E-yarn technology further (i.e., microcontrollers and full E-yarn circuits. In addition, the IMU E-yarn can also be used for other motion-related activities, such as gait (*fall and near-fall detection, E-textiles, wearables and motion tracking*).
- Designing, creating and proving the viability of an accurate, wearable textile fall and near-fall detection system that has considered the intended end users in the design process. The wider implications of this are using the detection system for home use or as an additional tool for risk assessments for falls. Furthermore, it shows another viable application of E-textiles (*design, fall and near-fall detection, healthy ageing and E-textiles*).
- Gaining insight into older adults' views on healthy ageing and technology for design, beneficial to E-textiles and wearable technology more generally. This can also be applied to designing for older adults and healthy ageing (*healthy ageing, E-textiles, and wearables*).
- Bridging the gap between technology and design in the E-textile field by using human-centred design to make E-textile garments for fall and near-fall detection. As well as showcasing the importance of collaboration *(design, E-textiles and fall and near-fall detection).*

7.3 Future Work

This thesis has designed and created an E-textile garment that has successfully been used for fall and near-fall detection. As the trials were conducted using young healthy female volunteers, the next logical step is to repeat these experiments with young healthy male volunteers. In addition, the stumble data presented in Chapter 5 is not a balanced dataset when compared to the ADL and fall datasets, therefore, it would be beneficial to repeat this study with further near-fall events, such as trips and slips, with both young males and females. The female and male data can be compared to determine if there are differences in the way that males and females fall and experience near-fall events. This information can be used to aid future designs of the near-fall detection E-textile and potentially help with developing strength training and balancing exercises for fall prevention programmes similar to the FaME toolkit [3] and Otago exercise programme [4] that are discussed in Chapter 1.

Furthermore, it is crucial to have people aged over 65 (the intended user group) test the garment. The simulation of falls, near-falls, and ADLs using young healthy volunteers does not show how older people move, as gait changes with age [5]. When looking at stumbling or any near-fall event, it would be best to collect the data in real-world situations. This is clearly difficult, but has been done in other studies [6,7], by allowing older people to wear the technology at home and report an instance of imbalance. In addition, it would be useful to collect ADL data from older adults and use the machine learning developed for younger adults to see if it can classify ADLs correctly. This would add the benefit of gaining feedback on the comfort of the garment. Moreover, as the interview and focus group data showed that multiple garments would be preferable, it would be constructive to develop more designs using a co-design approach. Each design will also need to be tested in real-world situations.

This thesis has shown the value of using an HCD approach to develop prototypes. Therefore, further investigation into the wants and needs of older men and women is required. The insights gained from the interviews will be used as a starting point to develop multiple prototypes that meet the needs of the target users, and this might be different for men and women. For example, when considering the size of the hardware, as women are more likely than men to develop arthritis as they age potentially making handling small hardware units difficult [8]. This should be followed by co-design workshops with the older adults to refine the prototypes and get feedback on the user experience. The interviews can be used more generally to understand the concerns of older adults about healthy ageing, as well as technology acceptance and sustainability. This type of research has been fairly limited in the fields of E-textiles and healthy ageing [9,10]. In addition, it would be useful to interview and collaborate with healthcare professionals to identify what they perceive to be detrimental to healthy ageing. This thesis has also shown the importance of collaboration in achieving the highest quality of research.

When considering the complexity of designing for older women (and potentially men) and the attitudes shown towards monitoring technology, the following questions are important to ask. Does the near-fall detection system have to be in an E-textile form? This technology could be incorporated into shoes, sandals, or slippers. If it is an E-textile, does it have to be worn every day or could it be given by a healthcare professional once a year to be worn for a week as a check-up device? Can it be used as an objective form of risk assessment rather than the current subject NICE guidelines [11]? Could it be used to enhance the NICE guidelines and are there special cases where such a device would be more useful? Otherwise, as people are living longer, they may have to wear a form of monitoring device from the age of 65 for potentially another 30 years. Another alternative would be to use the E-textile garment in care homes or retirement homes, which was suggested by participants from the focus group. Having older adults wear the device would easily alert healthcare professionals when someone has fallen. It would also allow for healthcare professionals to track the stability of someone over time and intervene before a fall can occur. Lastly, it could be used as a way to check if the older adults are still moving around and alert healthcare professionals to check in if movement behaviour changes.

To convince older adults, carers and care providers to buy E-textile garments for near-fall and fall detection, the design and marketing of the device needs to be carefully considered. The interview and focus group data showed an unwillingness to wear a monitoring device whilst participants consider themselves to be fit and healthy. The E-textile garment should be marketed as more than just a health monitoring device, such as a balancing training device. In addition, it would be useful to collaborate with experts in behavioural change to promote proactive healthy ageing. They can help to develop strategies to educate older adults on the risks of falls and how the E-textile garment can help them stay safe.

Other uses for this technology in E-textile form could be for gait monitoring. One study has already shown the use of an accelerometer E-yarn to measure gait [12], and this could be improved by using an IMU. As IMUs are commonly used for motion tracking, this IMU E-yarn could be used for other types of motion measurement. It could also be used for fitness tracking for athletes to enhance performance analysis and training and prevent injury. Moreover, by developing this IMU E-yarn, new knowledge has been generated to allow for the soldering of other complex components, which can be used to create other complex E-yarns.

The E-yarn technology itself needs to be tested for durability. Durability was not within the scope of this thesis. Previous work by the author [13] on washability of E-yarns has shown that the E-yarns can be washed multiple times and they will continue to work as long as they are line dried rather than tumble dried. When reviewing the failures of the E-yarns, the prevalent issue was the multi-strand copper wire being used. All other E-yarns are now made with Litz wire, which is more durable than the previously used multi-strand copper wire.

One of the biggest limitations to the E-textile prototypes shown in this work is the size of the supporting hardware module: This includes the microcontroller used to control sensors and the power supply. A commercial off-the-shelf microcontroller has been used so far.

Furthermore, the IMU in the manufacturing of the E-yarn in this thesis required a small signal conditioning print circuit board (PCB). This PCB could be made smaller or even flexible. Ideally, the capacitors used to smooth the signal should be incorporated into the E-yarn in the future. The microcontroller can be a bespoke circuit design like in any smartwatch and therefore be made much smaller. As the thesis has shown that complex sensors can be used in the E-yarn, the implication is that the microcontroller can also be made using the E-yarn technology. An E-textile comprised of entirely E-yarn technology would be the ideal way to move the E-textile field forward. Furthermore, the interfacing, data collection, communication, and security of data need to be considered in the design of E-textiles. This work has allowed for Bluetooth communication and remote storage of data, which are important steps towards developing fully integrated E-textile systems.

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APPENDIX

A. CHAPTER 3

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Nottingham Trent University Schools of Art and Design, Arts and Humanities and Architecture, Design and the Built Environment Research Ethics Committee of Nottingham Trent University (protocol code 2019/20-46 and date of approval 30/03/2022).

A.1 CONSENT FORM

CONSENT FORM PROFORMA

Dear Research Participant,

The population of the world is ageing, and it is creating a significant impact on the health and social care systems. Ageing is linked with frailty and a major risk factor of this is falling. Near falls are a precursor to falling and occur more often. Therefore, the ability to remotely monitor near falls and falls will help prevent injury and therefore will reduce pressure on hospitals and care homes. Wearable technology provides a solution to remotely monitor falls and near falls in real-time and non-invasively. The purpose of this study is to develop wearable technology, in the form of electronic textiles, for fall and near fall detection.

All participation in the project is voluntary. If you do you agree to be part of this project, we would like to use the information to develop reports, a thesis, presentations, and publications; but your name and identity will remain anonymous. All recordings will be stored securely and remain confidential. If you decide at any stage, you no longer want to be part of the project, just let us know within two weeks and we will make sure any information you have given us is destroyed.

This project has been reviewed by, and received ethics clearance through, the Nottingham Trent University College of Art, Architecture, Design and Humanities Research Ethics Committee

Please read and agree to the following statements:

I have read the above project description and had an opportunity to ask questions about the research and received satisfactory answers to any questions.
I have had sufficient information to decide whether or not I wish to take part in the study.
I understand that I am free to withdraw from the research within two weeks by informing the researcher of this decision.
I understand that my personal information will be treated in the strictest confidence.
I understand that the results of the experiments will be included in in material published from this research.
I am willing to partake in the various activities required for this research project.
I agree to have video recordings made during this study and understand that the anonymised versions these recordings made publicly available.
I understand that anonymized data, which cannot identify me, will be publicly available in line with the University Research Data Management Policy.

Full Name ______________________________

Date ______________________________

If you have any questions please contact ……………………………..

A.2 Participant Information Sheet

NOTTINGHAM TRENT UNIVERSITY
Proforma: Research Consent Information Sheet

Protocol Title	Near fall detection using wearable sensors and electronic textiles
Principal Investigator	Zahra Rahemtulla
Project Group	Advanced Textiles Research Group
Supported By	Professor Jake Kaner

What is the purpose of this study?

The overall aim of this study is to develop technology for near fall detection using electronic textiles. More specifically the best sensor or combinations of sensors, as well as the correct location for the(se) sensor(s) on the body need to be determined so that the differences between a fall, a near fall and activities of daily living (ADLs) can be distinguished.

What are we asking you to do?

We would like you to walk around the lab and to perform various exercises wearing multiple sensors that are placed on different locations of your body. Some of these will be commercially available sensors, and some might be electronic textiles. At the same time, we will be video recording your movements as a validation of the technology.

The activities that we will ask you to perform are walking, sitting on a chair, timed up and go test (standing from seated, walking and returning to seated), a controlled stumble and three types of falls onto a crash mat, you will be asked if you are comfortable to do this before the study.

In addition to taking data about your we will need height and weight measurements, to ask you about the comfort of the sensor and we will need to record your age and gender.

How we would like to use the information provided

The data that we collect will be used to determine if the prototype developed can distinguish the differences between a fall, a near fall, and activities of daily living (ADLs).

Compliance with the Research Data Management Policy

Nottingham Trent University is committed to respecting the ethical codes of conduct of the United Kingdom Research Councils (RCUK) and EU GDPR. Thus, in accordance with procedures for transparency and scientific verification, the University will conserve all information and data collected during the experiments in line with University Policy, consistent with both RCUK, and the EU GDPR, (https://www.ukri.org/about-us/policies-and-standards/gdpr-and-research-an-overview-for-researchers/).

All data will be anonymised and, with your consent, made publicly available for anybody (including researchers, businesses, governments, charities, and the general public) to use.

What are the possible risks or discomforts?

Your participation does not involve any risks other than what you would encounter in daily life. If you are uncomfortable with any of the questions or activities you are free to not answer or participate.
What are my rights as a research participant?
Your participation in this project is entirely voluntary: • You have the right to withdraw your consent and participation at any moment: before, during, or after up to a period of two weeks. If you do wish to withdraw your consent please e-mail me at n0842040@ntu.ac.uk • You have the right to remain anonymous in any write-up (published or not) of the information generated during this study. • You have the right to refuse to answer to any or all of the questions you will be asked. You also have the right to specify which exercises you are willing to perform. • You have the opportunity to ask questions about this research and these should be answered to your satisfaction. If you want to speak with someone who is not directly involved in this research, or if you have questions about your rights as a research subject, contact Professor Michael White, Chair for the College Research Ethics Committee (CREC) for the College of Art Architecture Design and Humanities (CAADH) at Nottingham Trent University. You can call him at 0115 848 2069 or send an e-mail to michael.white@ntu.ac.uk.
What about my Confidentiality and Privacy Rights?
Unless required by law, only the study investigator and members of NTU staff have the authority to review your records. They are required to maintain confidentiality regarding your identity. Results of this study may be used for teaching, research, publications, and presentations at professional meetings. If your individual results are discussed, then a code number or a pseudonym will be used to protect your identity.
Audio/visual recordings
Any recorded data will be kept confidential and in a secure place in line with the Research Data Management Policy and destroyed in line with the current RCUK/University/GDPR Guidelines. Any of the recorded data and images will be taken by avoiding the face and where this is not possible the face will be blurred.
Who should I call if I have questions or concerns about this research study?
Professor Jake Kaner

A.3 Other Participant Data

This section presents data from four other participants as a comparison to the data presented above. This is important to show that the patterns seen are reproduced in each participant. The results shown only present data from two locations (ankle and wrist) and four activities (kneeling, 'Timed Up and Go', reaching high to low and falling. The locations were chosen as the wrist did not present consistent data between participants and the ankle, like the other locations showed similar patterns for each participant.

All the participants were asked to attach the trackers to themselves, due to COVID healthy and safety guidelines. Therefore, the graphs below show different orientations of the three axes. However, this does not take away from that the fact that the patterns observed for activities between the participants were fairly similar. Additionally, each participant performed the activities differently and over a slightly different timeframe.

A.3.1 Ankle

Figure A.1 to Figure A.8 present the acceleration and gyroscope data for the participants taken at the ankle for each activity (kneeling, 'Timed Up and Go', reaching high to low and falling.

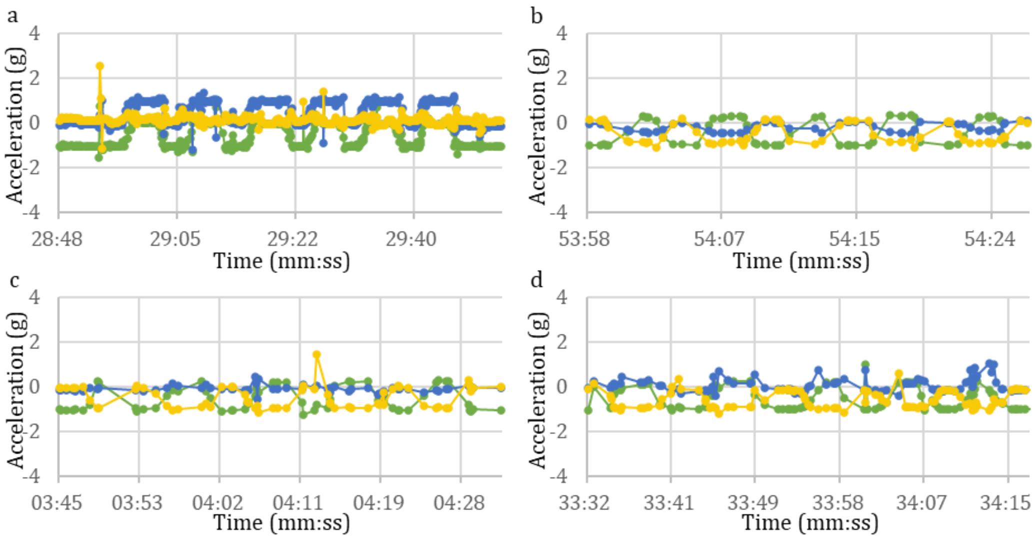

Figure A.1 Acceleration data taken at the ankle for the kneeling activity. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

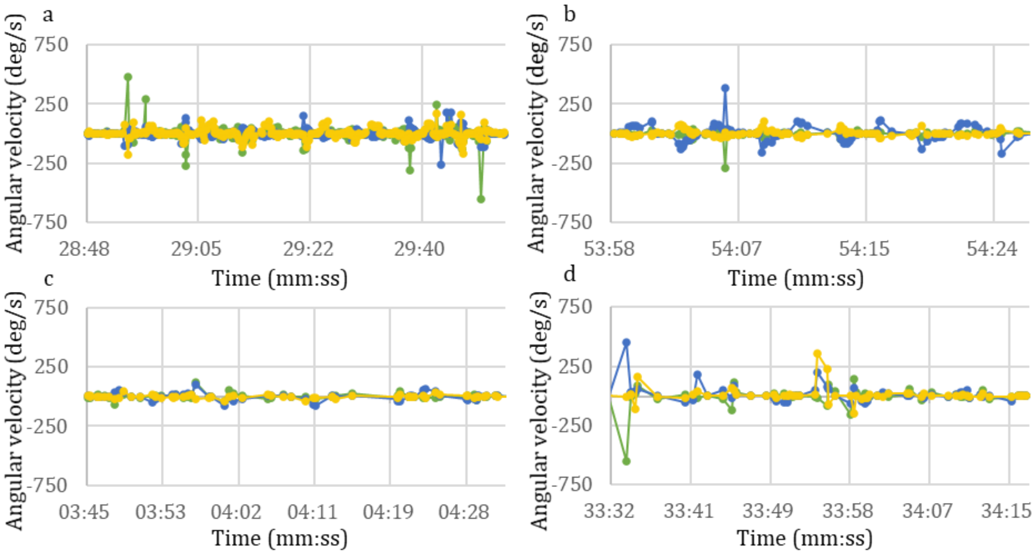

Figure A.2 Gyroscope data taken at the ankle for the kneeling activity. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

Figure A.1 showed the accelerometer data for kneeling and the patterns shown here matched the ones seen in Figure 3.51a. Figure A.2 showed the gyroscope data, which has similar patterns to Figure 3.51b.

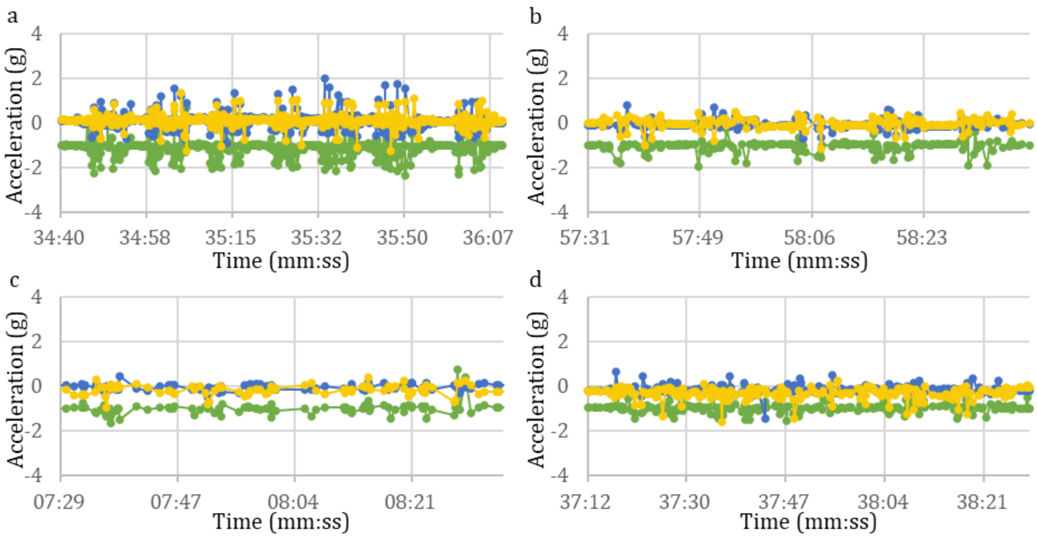

Figure A.3 Acceleration data taken at the ankle for the 'Timed Up and Go' test. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

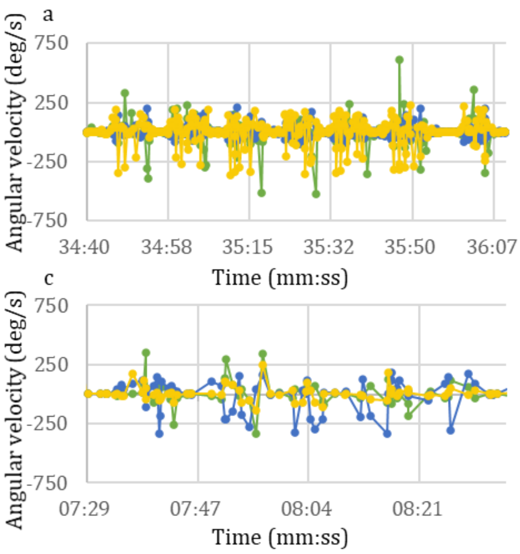

Figure A.4 Gyroscope data taken at the ankle for the 'Timed Up and Go' test. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

Both the accelerometer data in Figure A.3 and the gyroscope data in Figure A.4 followed the same patterns seen in Figure 3.54 (participant one). The turns were clearly visible in Figure A.4 for all participants.

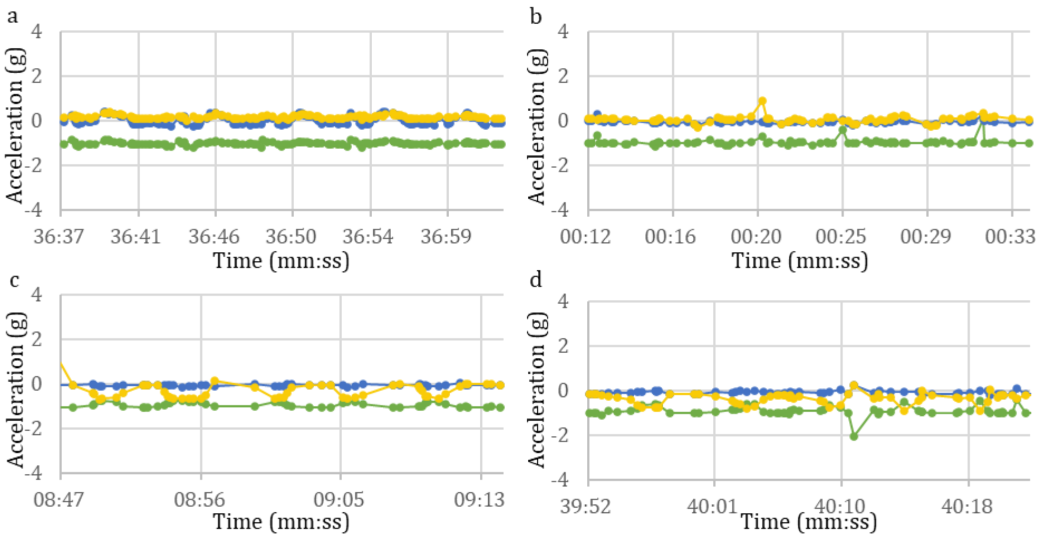

Figure A.5 Acceleration data taken at the ankle for reaching high to low. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

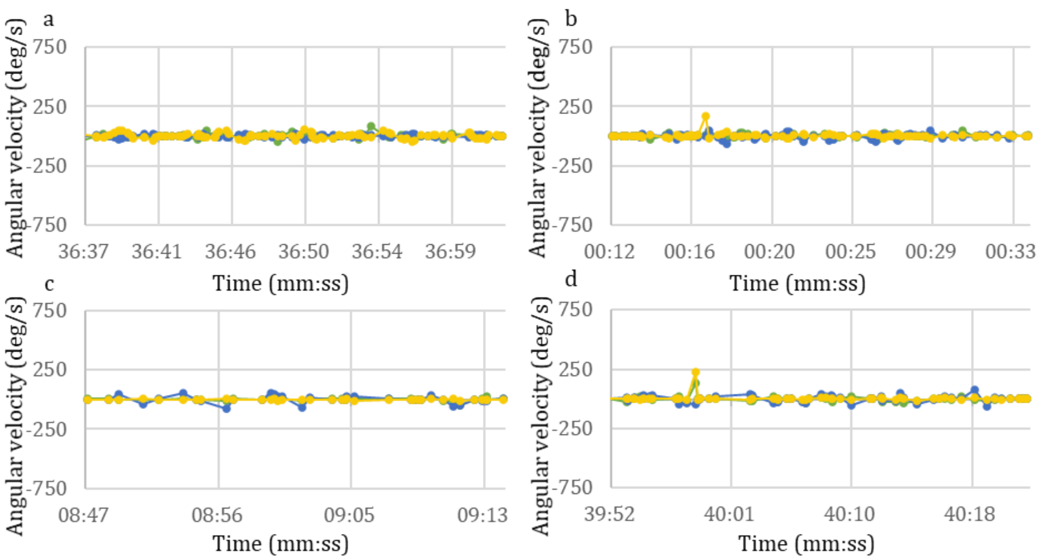

Figure A.6 Gyroscope data taken at the ankle for reaching high to low. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

Figure A.5 showed the accelerometer data for reaching high to low activity. In Figure A.5a and b, it was much less clear when the actions are taking place compared to Figure A.5c and d given a much lower acceleration in the z-axis. The gyroscope data followed the same patterns that were seen for participant one (Figure 3.52b).

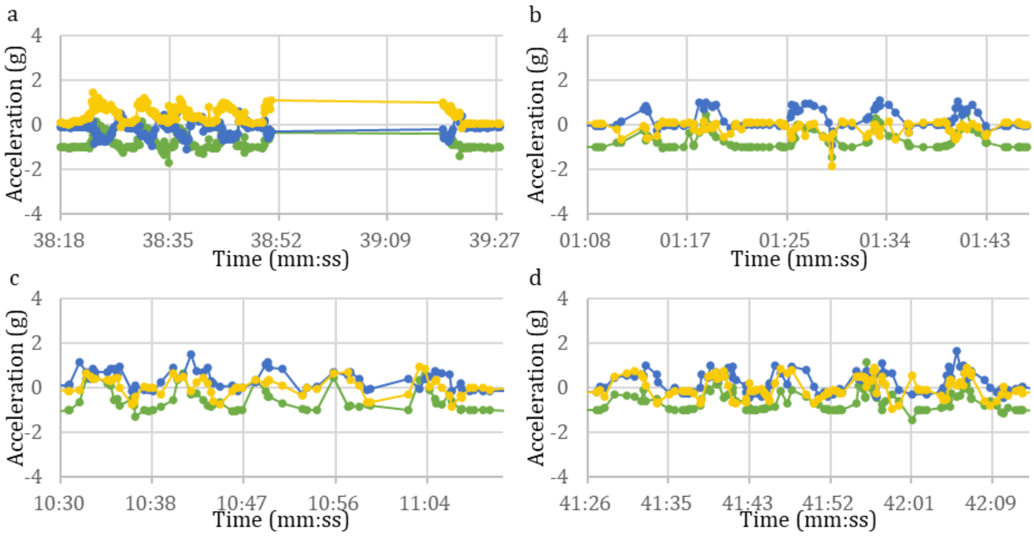

Figure A.7 Acceleration data taken at the ankle for the fall. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

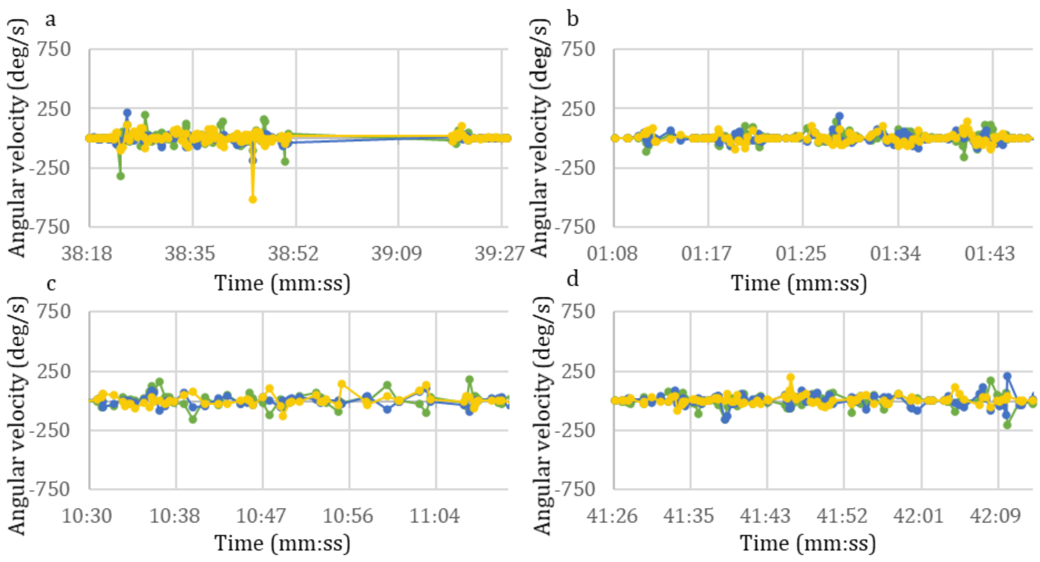

Figure A.8 Gyroscope data taken at the ankle for the fall. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

The fall data had a pattern that was similar to the one seen for participant one in Figure 3.56. There are large changes in the acceleration in all three axes, as seen for participant one. Additionally, the gyroscope data does not have a clear pattern for the fall, but only in Figure A.8b is easy to distinguish between the fall and being still. Figure A.7a and Figure A.8a showed a reduction in the sampling rate between the fourth and fifth repeat.

A.3.2 Wrist

The graphs presented in Figure A.9 to Figure A.16 show the acceleration and gyroscope data taken at the wrist for the other four participants for each activity (kneeling, 'Timed Up and Go', reaching high to low and falling).

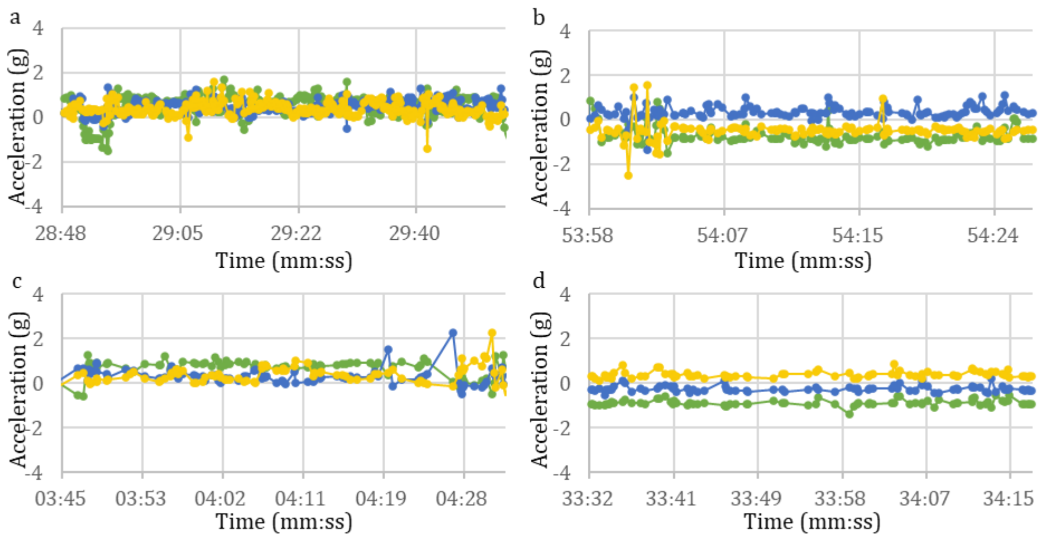

Figure A.9 Acceleration data taken at the wrist for the kneeling activity. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

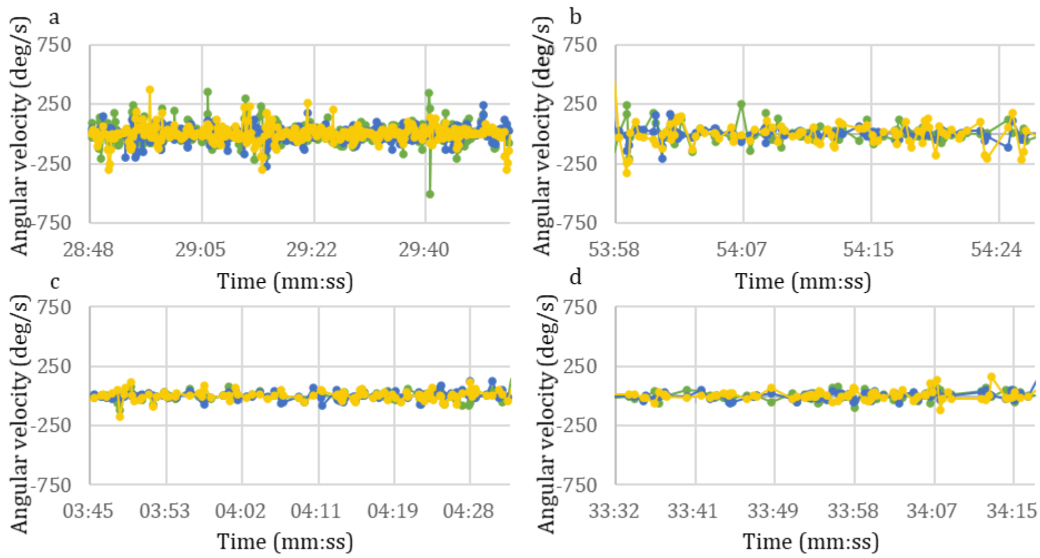

Figure A.10 Gyroscope data taken at the wrist for the kneeling activity. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

Figure A.9 and Figure A.10 showed the accelerometer data and gyroscope data at the wrist for the kneeling activity. The figures agreed with Figure 3.61, as they do not show any clear patterns for the activity.

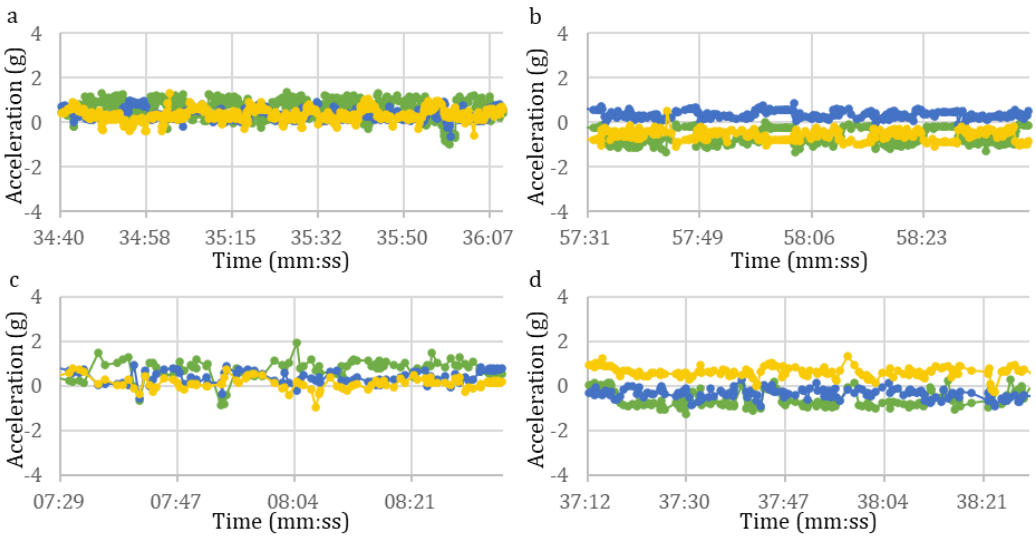

Figure A.11 Acceleration data taken at the wrist for the 'Timed Up and Go' test. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

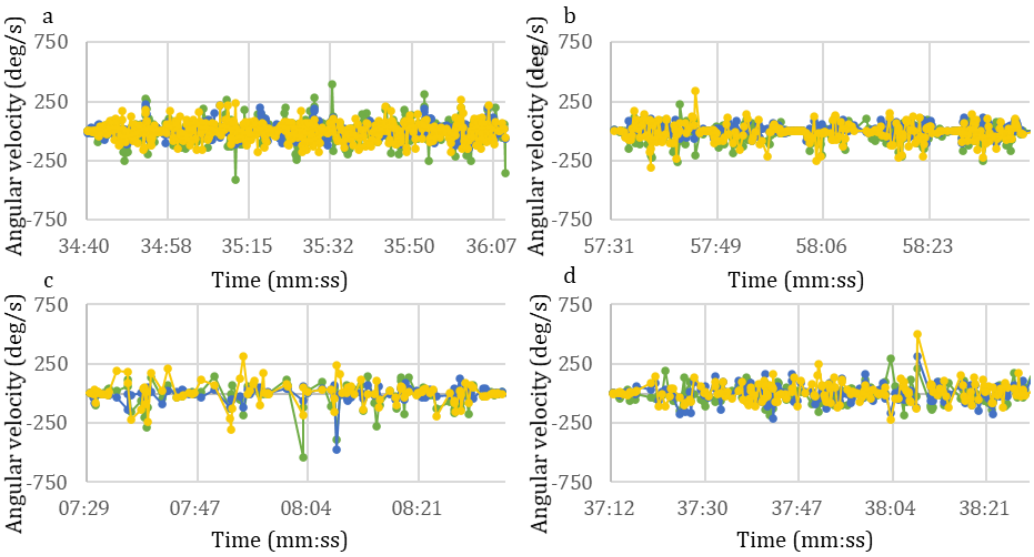

Figure A.12 Gyroscope data taken at the wrist for the 'Timed Up and Go' test. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

Figure A.11 and Figure A.12 showed the accelerometer data and gyroscope data at the wrist for the activity 'Timed Up and Go' test. The figures agreed with Figure 3.64, as they do not show any patterns for the activity.

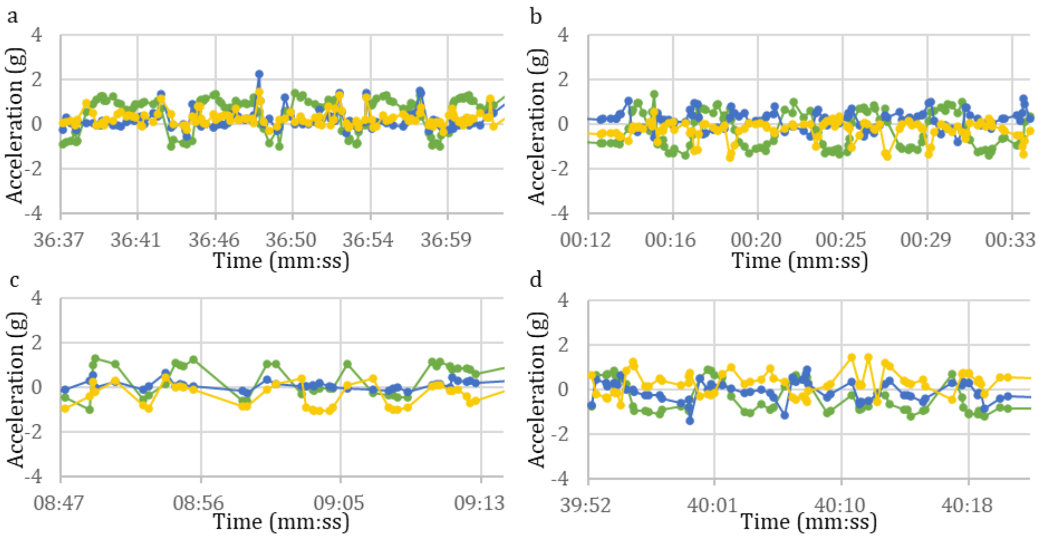

Figure A.13 Acceleration data taken at the wrist for reaching high to low. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

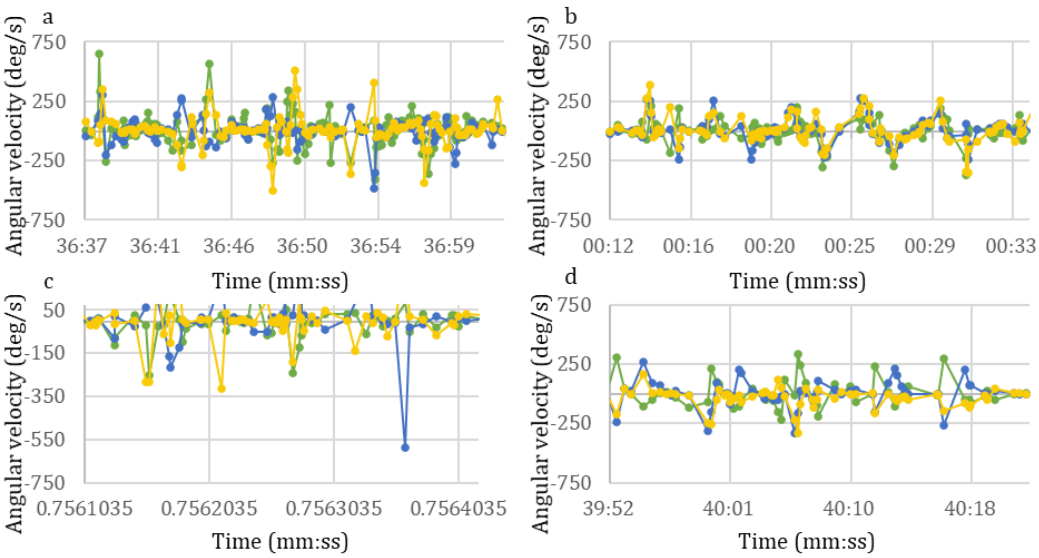

Figure A.14 Gyroscope data taken at the wrist for reaching high to low. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

Figure A.13 and Figure A.14 showed the accelerometer data and gyroscope data at the wrist for the activity of kneeling. The figures agreed with Figure 3.62, with the pattern showing when the participants reached their hand up and down.

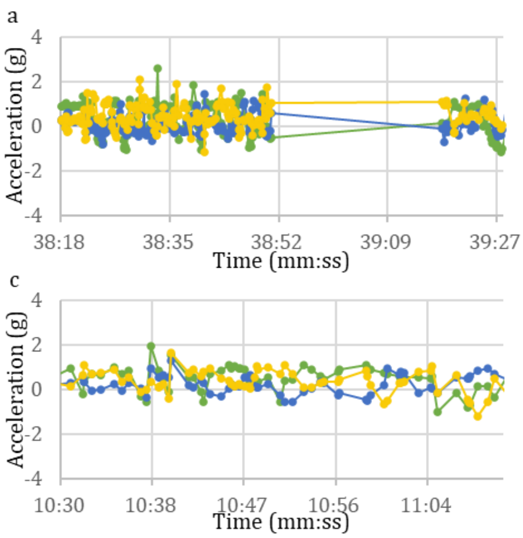

Figure A.15 Acceleration data taken at the wrist for the fall. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

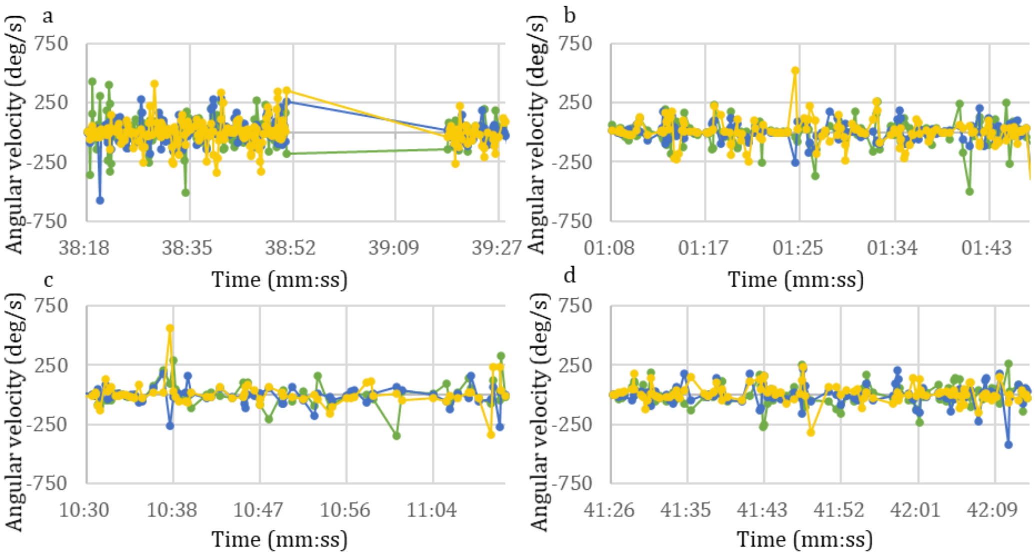

Figure A.16 Gyroscope data taken at the wrist for the fall. (a) Participant two, (b) participant three, (c) participant four and (d) participant five. x-axis, y-axis and z-axis.

Detecting falls at the wrist did show a pattern in the accelerometer data (Figure A.15), which was in agreement with participant one's data in Figure 3.66a. However, the patterns were not the same for each participant (unlike with the other activities). Additionally, Figure A.15a and Figure A.15c have lower sampling rates which do make it harder to differentiate between the fall and the stillness. The gyroscope data in Figure A.16 also showed no clear patterns, as seen in Figure 3.66b.

A.4 Validation Trials

As presented in Appendix A.3 Other Participant Data, it is clear that the sampling rate of the MetaTracker affected the patterns. Therefore, the data has been validated using the Bosch application board with the BMI160 as described in Section 3.2.2. The experiments were performed with one participant as the results above show that the patterns are consistent between the participants. The activities performed were walking, kneeling, reaching high to low, 'Timed Up and Go' and lying down. These were chosen as they showed a variety of the patterns observed. The MetaTracker location for this set of experiments was the thigh, ankle and waist. This is because of the three centres of gravity locations (chest, waist and lower back), the waist was the most reliable and deemed best for designing the final E-textile garment. The thigh showed the most information, and the ankle shows the feet movement more than any other location. In the user trials, a MetaTracker was attached to each location and the data was collected simultaneously. For the validation trials, only one MetaTracker was used at a time. At the thigh, sampling rates of 25Hz, 50Hz and 100Hz were used, to test the limits of the MetaHub, and as a comparison to the Bosch system as well as to find the most suitable sampling rate.

A.4.1 Waist

Figure A.17 to Figure A.21 present the data taken at the waist for walking, kneeling, 'Timed Up and Go' and lying down. These are a comparison of the data from the user trials in Section 3.3.2 and the validation data.

A.4.1.1 Walking

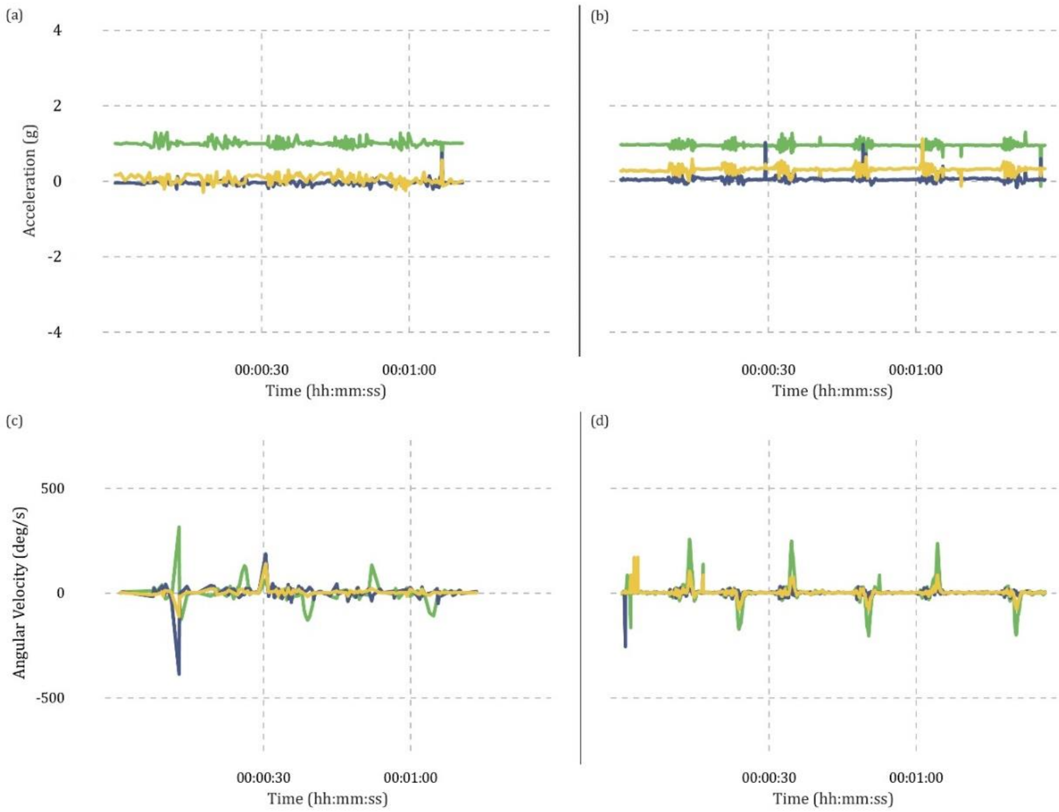

Figure A.17 Data taken at the waist using the MetaTracker for the walking activity. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.17 showed that the patterns observed for the original data set and the validation dataset were the same for both acceleration and angular velocity. The changes in acceleration for both datasets are the same however the turns that can be seen in the angular velocity have a larger change in the validation data. This is most likely due to how quickly the participant turned.

A.4.1.2 Kneeling

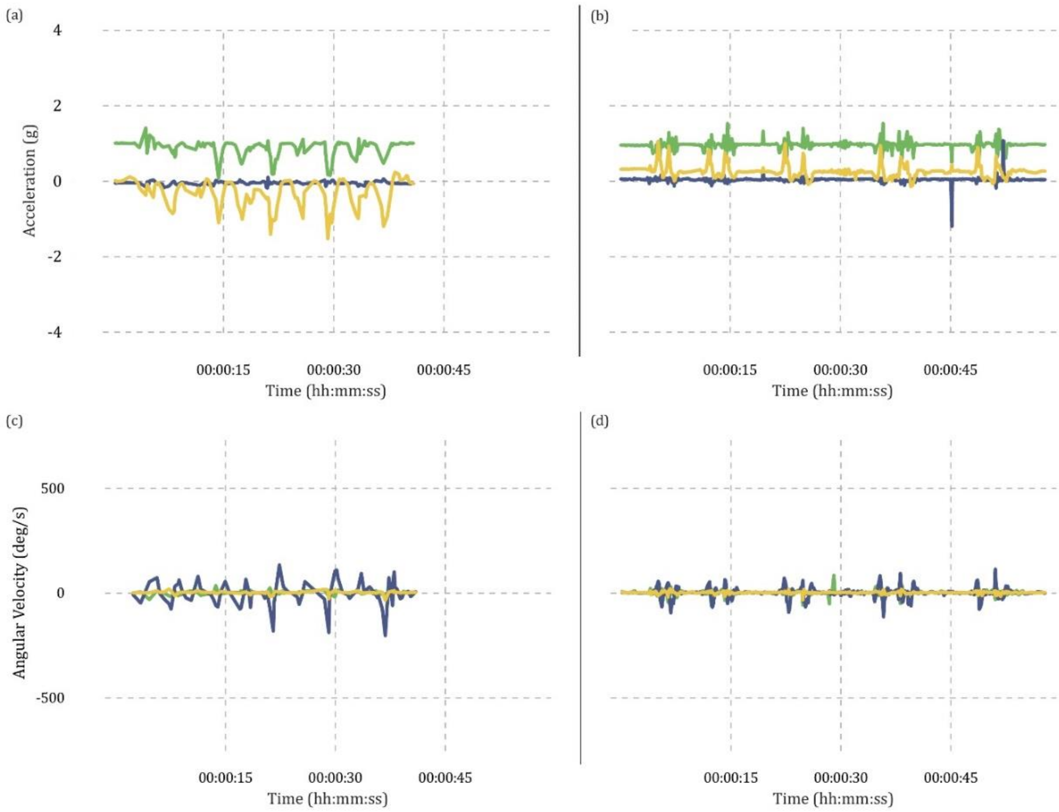

Figure A.18 Data taken at the waist using the MetaTracker for the kneeling activity. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.18 showed that the validation data had the same patterns as the original data, however, the acceleration was in the opposite direction (the device was worn in a different orientation). Additionally, the change in acceleration and angular velocity was smaller for the validation data.

A.4.1.3 High to low

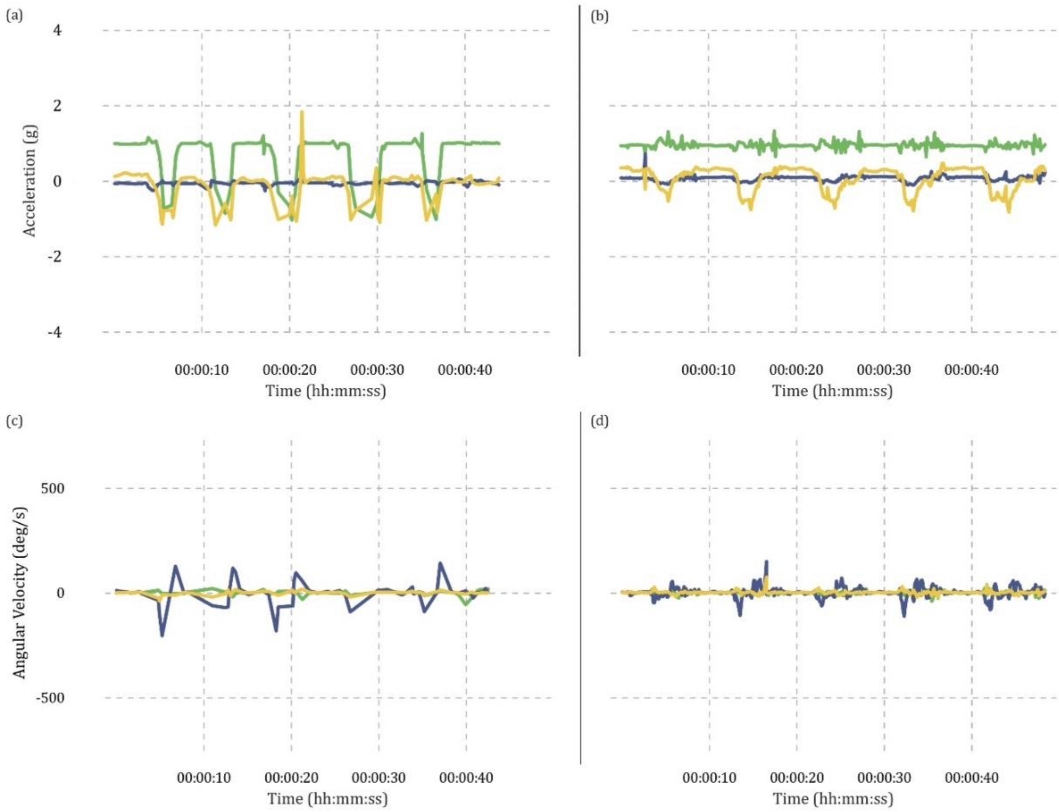

Figure A.19 Data taken at the waist using the MetaTracker for reaching high to low. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.19 showed a similar pattern for the original and validation data. The change in acceleration is smaller for the validation data and the x-axis does not have the same large change in acceleration observed in the user trials.

A.4.1.4 'Timed Up and Go'

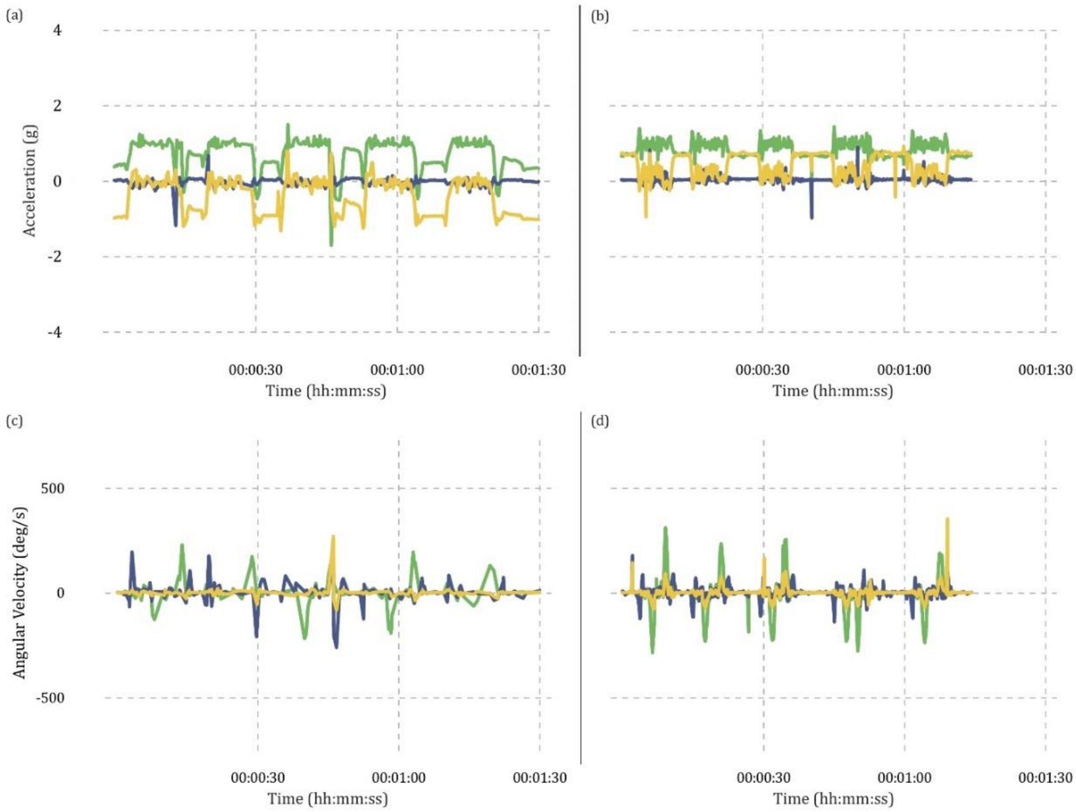

Figure A.20 Data taken at the waist using the MetaTracker for the 'Timed Up and Go' test. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.20 showed the same patterns for both the original and validation data, however, the turns seen in the gyroscope data were larger in the validation dataset. Additionally, a small change was seen in the z-axis during each turn. The acceleration showed the same pattern yet has smaller changes in acceleration as the participant stands and sits.

A.1.4.5 Lying Down

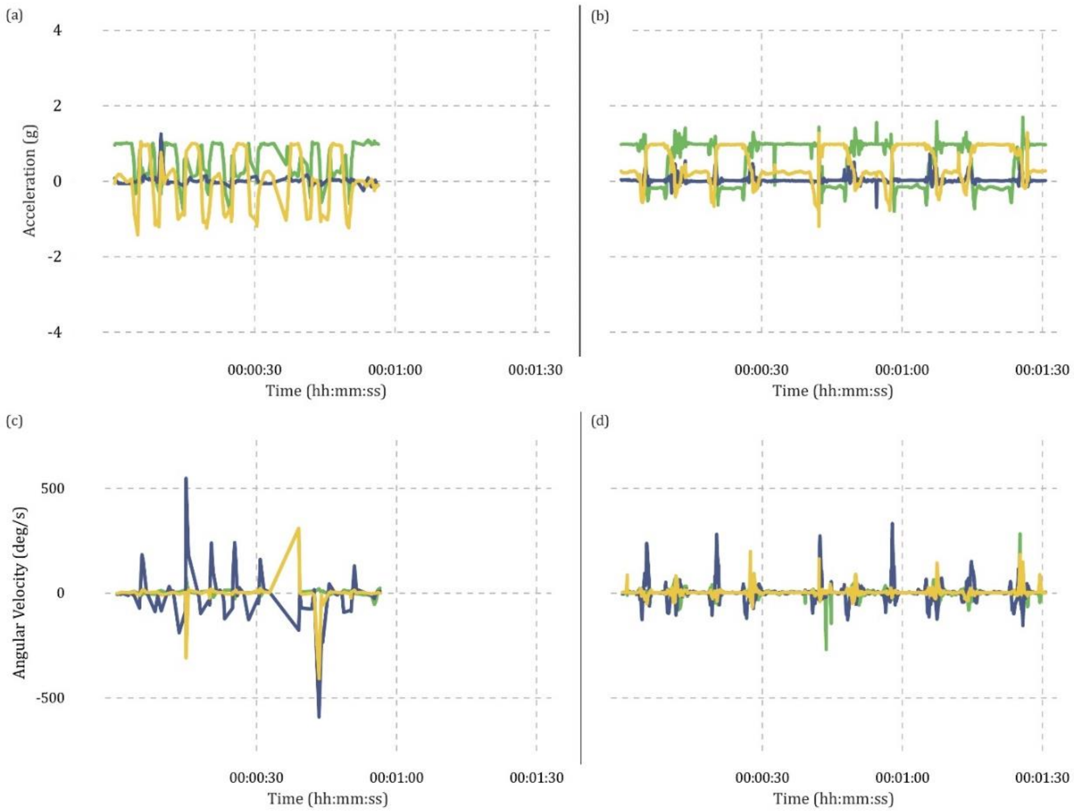

Figure A.21 Data taken at the waist using the MetaTracker for lying down. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.21 showed smaller changes in the acceleration data for the validation experiments and much clearer patterns in the angular velocity data. This was most likely due to the fact that there were more data points. The pattern showed a large increase in the angular velocity in the y-axis as the participant laid down compared to when they rose.

A.4.2 Ankle

Figure A.22 to Figure A.26 show the data taken at the ankle for walking, kneeling, 'Timed Up and Go' and lying down. These are a comparison of the data from the user trials in Section 3.3.3 and the validation data.

A.4.2.1 Walking

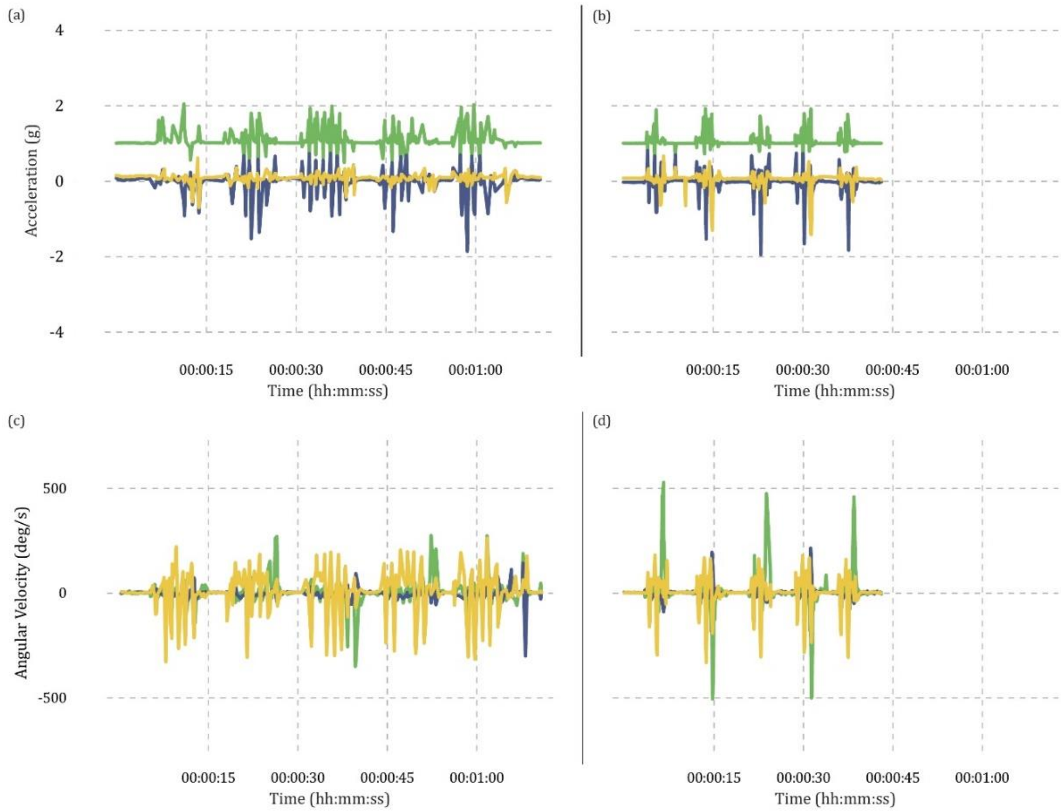

Figure A.22 Data taken at the ankle using the MetaTracker for the walking activity. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.22 showed that the original and validation datasets were similar. The gyroscope data in Figure A.22d showed a larger change in the angular velocity for the turns. Additionally, during repeats 2 and 3 of the validation data, when there was a decrease in the angular velocity on the x-axis there is an associated decrease in the acceleration on the z-axis (Figure A.22d).

A.4.2.2 Kneeling

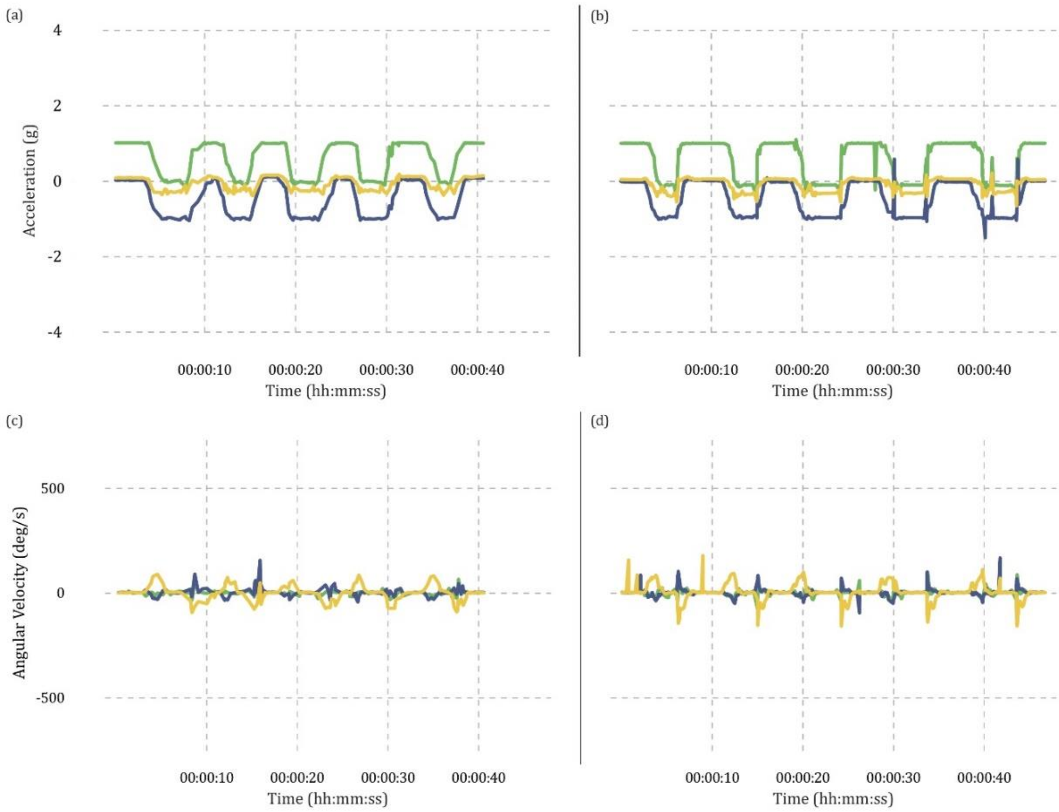

Figure A.23 Data taken at the ankle using the MetaTracker for the kneeling activity. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.23 showed the same pattern for original and validation data. The shape in the acceleration data is more defined in Figure A.23b.

A.4.2.3 High to low

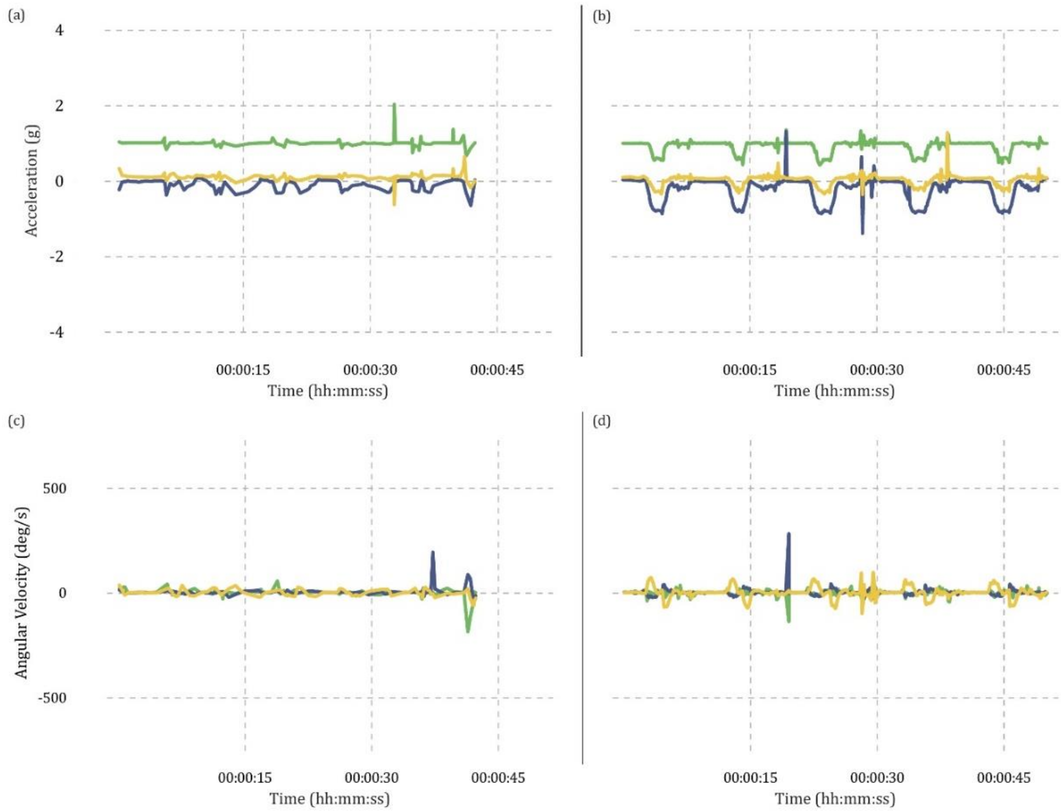

Figure A.24 Data taken at the ankle using the MetaTracker for reaching high to low. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Data from the validation in Figure A.24b and d were much clearer than before. In the acceleration data, there is a larger change in acceleration in all three axes as the activity was taking place. This was the same in the gyroscope data, where larger changes in angular velocity were observed. There was an increase and then a decrease in the angular velocity in the z-axis that was larger than before. Additionally, it was much easier to distinguish the activity where, the y-axis and x-axis have opposing changes in angular velocity, and it is smaller (similar to what was seen during the kneeling activity).

A.4.2.4 'Timed Up and Go'

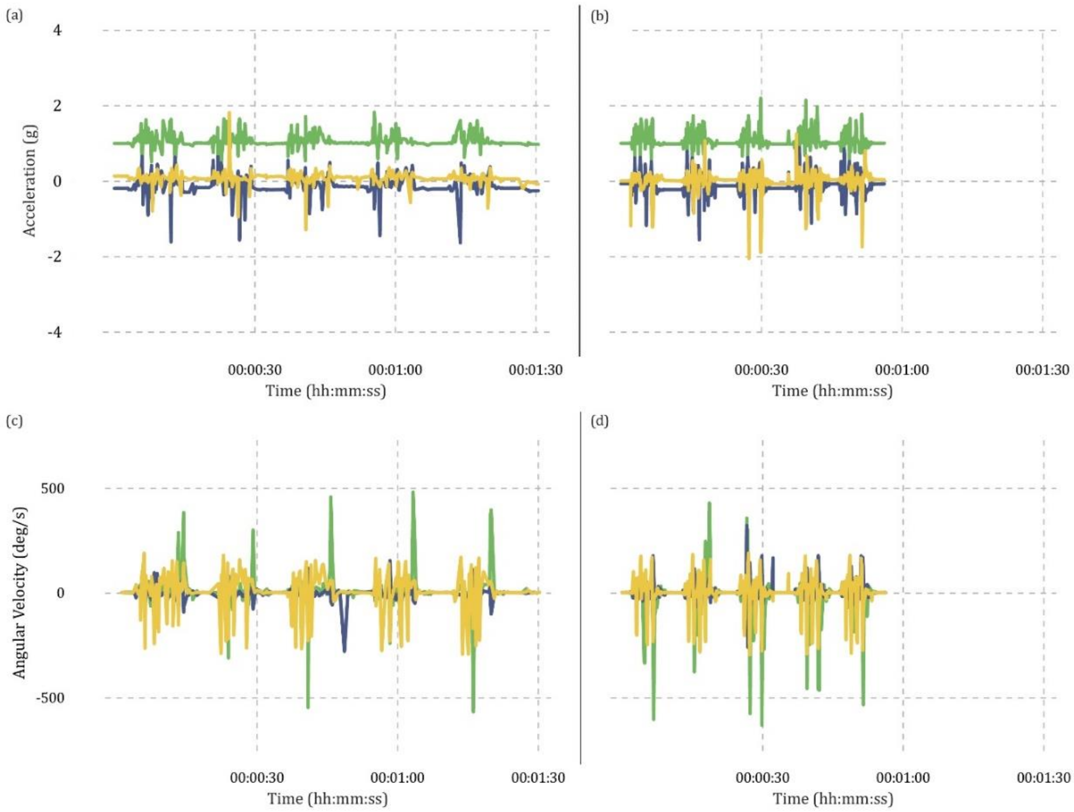

Figure A.25 Data taken at the ankle using the MetaTracker for the 'Timed Up and Go' test. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

The patterns observed in the original and validation data were very similar. The validation data seemed to have a more accurate sampling rate. Additionally, in the gyroscope data for the validation experiments, when there is a decrease in the angular velocity in the x-axis the acceleration in the z-axis showed a large change, similar to the pattern seen in Figure A.22d, as the participant turned.

A.4.2.5 Lying Down

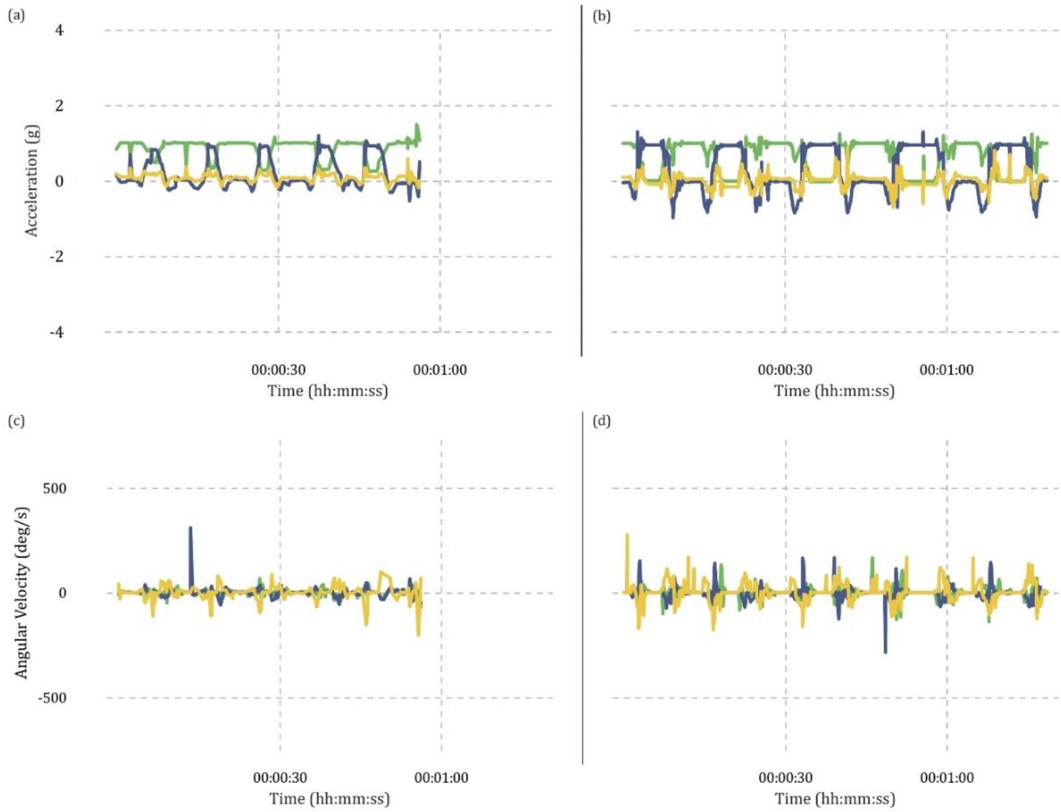

Figure A.26 Data taken at the ankle using the MetaTracker for lying down. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.26a and b showed that the original data and validation data have slightly different patterns. As the participant was standing up the acceleration increased in the x-axis, decreased in the y-axis, and decreased then increased in the z-axis which ended at the same point for standing and lying down. As the participant was lying down there was a decrease in the x-axis, a decrease then an increase in the y-axis, and a decrease then an increase in the z-axis, like for standing up. The validation data looked similar to the original data but was given slightly bigger changes in the acceleration.

Figure A.26c and d showed that there were also larger changes in angular velocity for the validation data, but a similar pattern in the z-axis showing an increase in the angular velocity, then a decrease, as the participant laid down and as the participant stood up.

A.4.3 Thigh

Figure A.27 to Figure A.31 present data from the thigh for walking, kneeling, 'Timed Up and Go' and lying down. These are a comparison of the data from the user trials in Section 0 and the validation data.

Figure A.32, Figure A.33 and Figure A.34 show the data taken at the thigh for lying down at 25Hz, 50Hz and 100Hz respectively. They are also a comparison of the validation data and the data collected using the Bosch system. The orientation of the Bosch sensor on the application board is different to the MetaTracker, therefore during the comparison it is important to note that the z-axis for the Bosch sensor shows the same patterns as the x-axis for the MetaTracker.

A.4.3.1 Walking

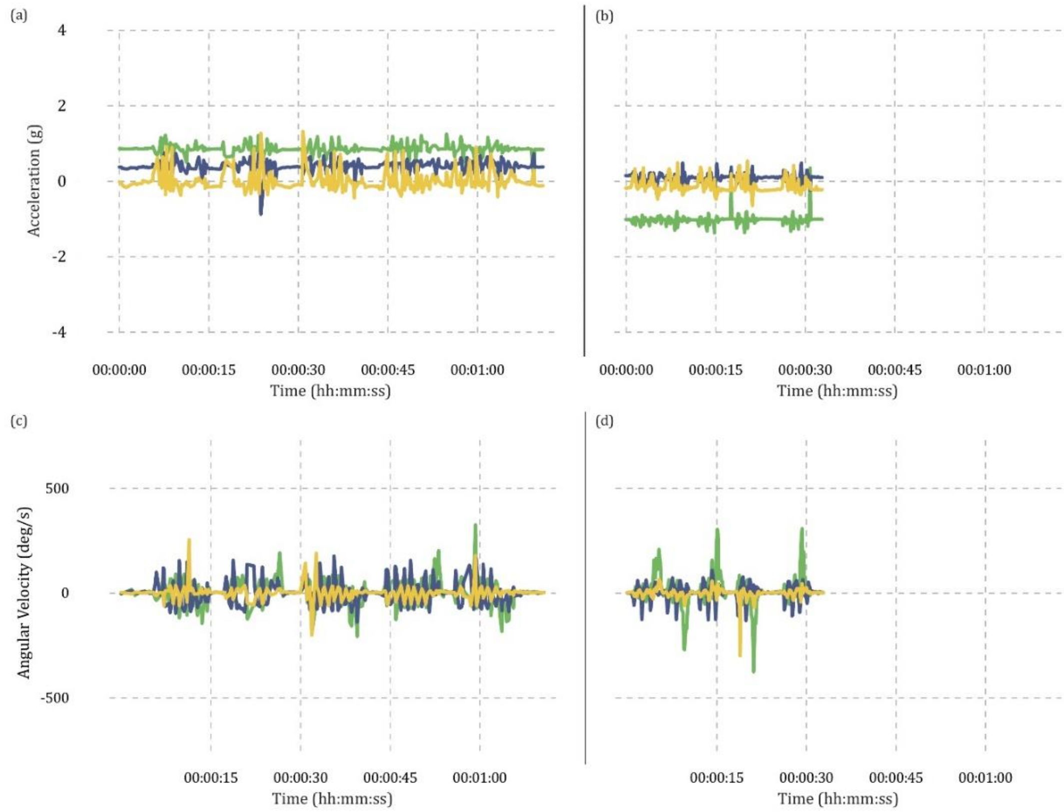

Figure A.27 Data taken at the thigh using the MetaTracker for the walking activity. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

The validation data showed smaller changes in acceleration for walking, however in the gyroscope data the turns tend to have a larger change in angular velocity, in the x-axis, compared to the MetaTracker. This is possibly due to the participant walking smoother and for a shorter distance in the validation experiments.

A.4.3.2 Kneeling

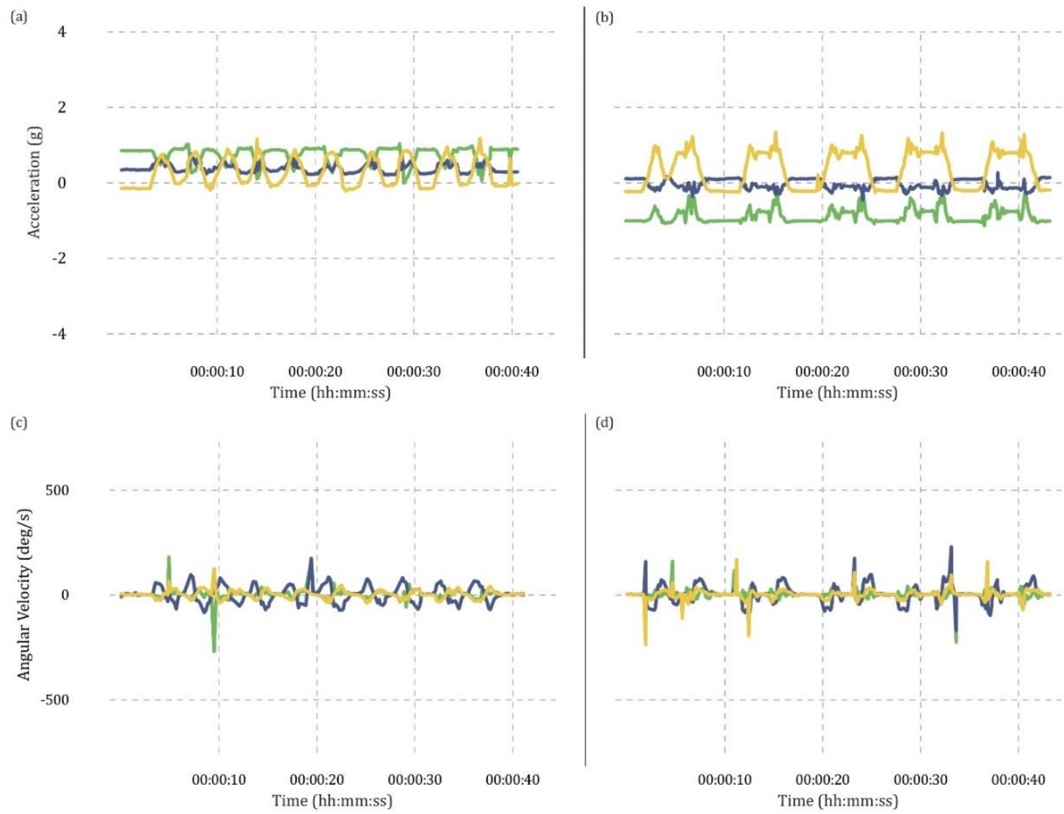

Figure A.28 Data taken at the thigh using the MetaTracker for the kneeling activity. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.28 showed the same pattern for both the original and validation data, however, there were larger changes in all of the axes for the acceleration and angular velocity in the validation data.

A.4.3.3 High to low

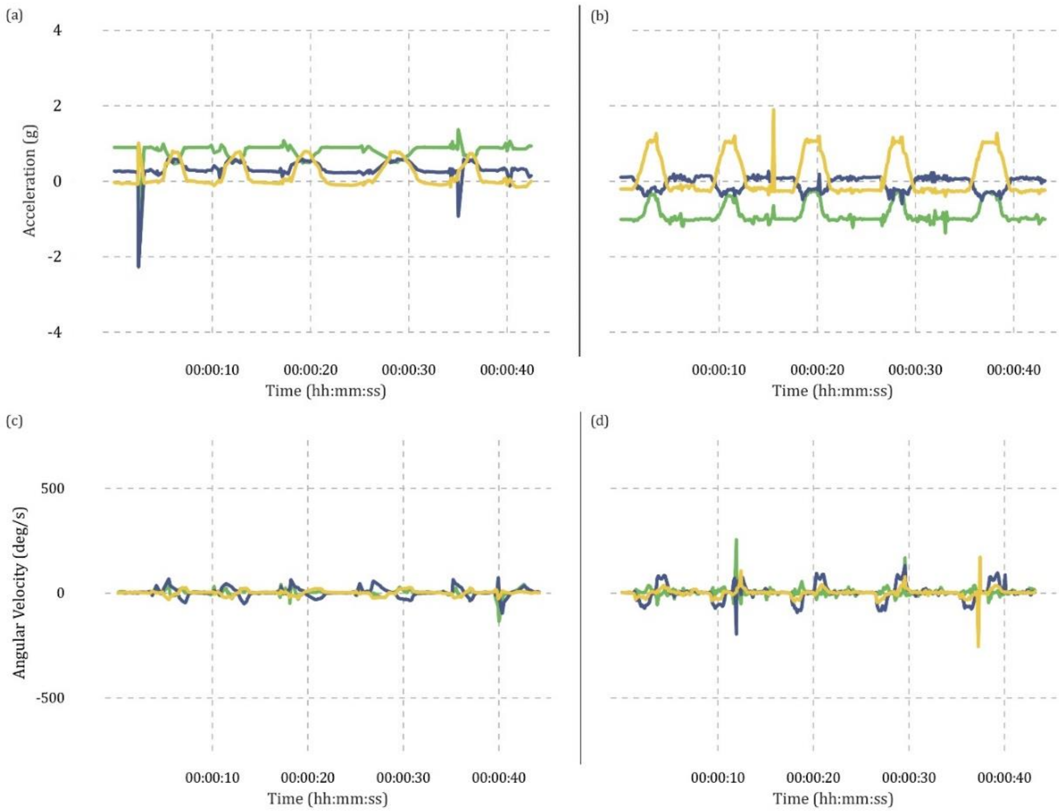

Figure A.29 Data taken at the thigh using the MetaTracker for reaching high to low. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.29 showed the same pattern for both the original and validation data. However, there were larger changes in all of the axes for acceleration and angular velocity in the validation data. These larger changes made the validation data clearer to interpret.

A.4.3.4 'Timed Up and Go'

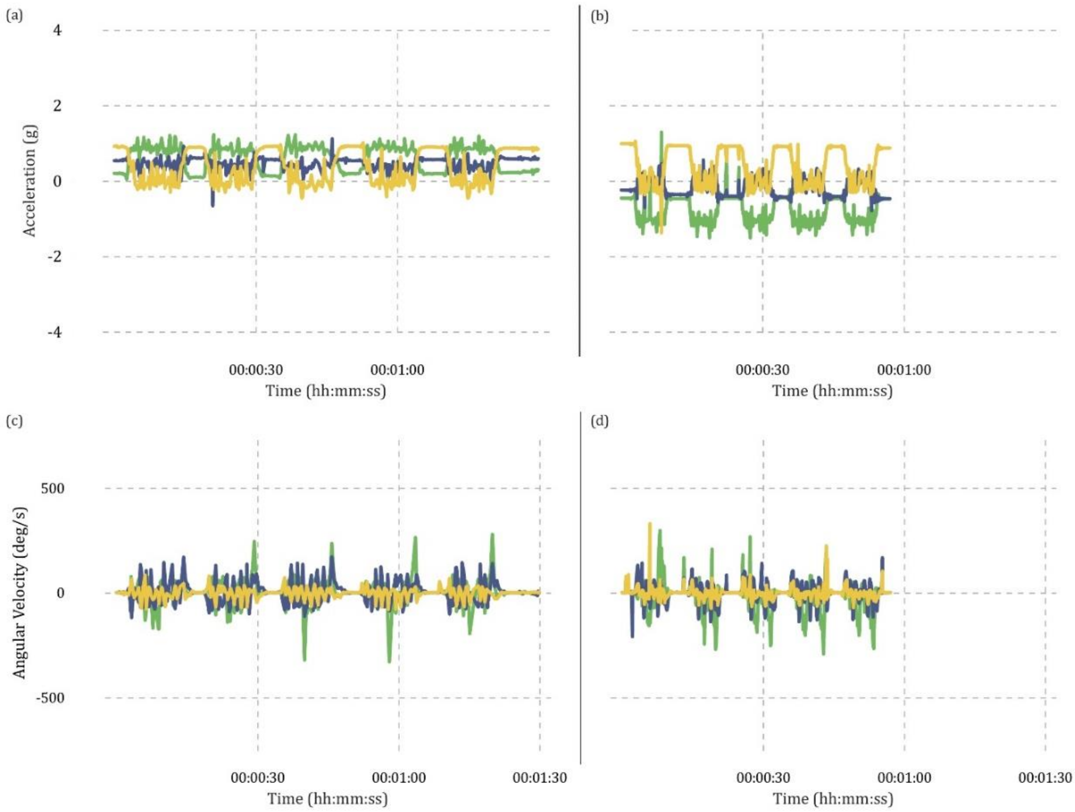

Figure A.30 Data taken at the thigh using the MetaTracker for the 'Timed Up and Go' test. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.30 showed the same pattern for both the original and validation data but with larger changes in all axes for acceleration and angular velocity observed. It is also clearer to see the turns in the validation data given the high magnitudes recorded.

A.4.3.5 Lying Down

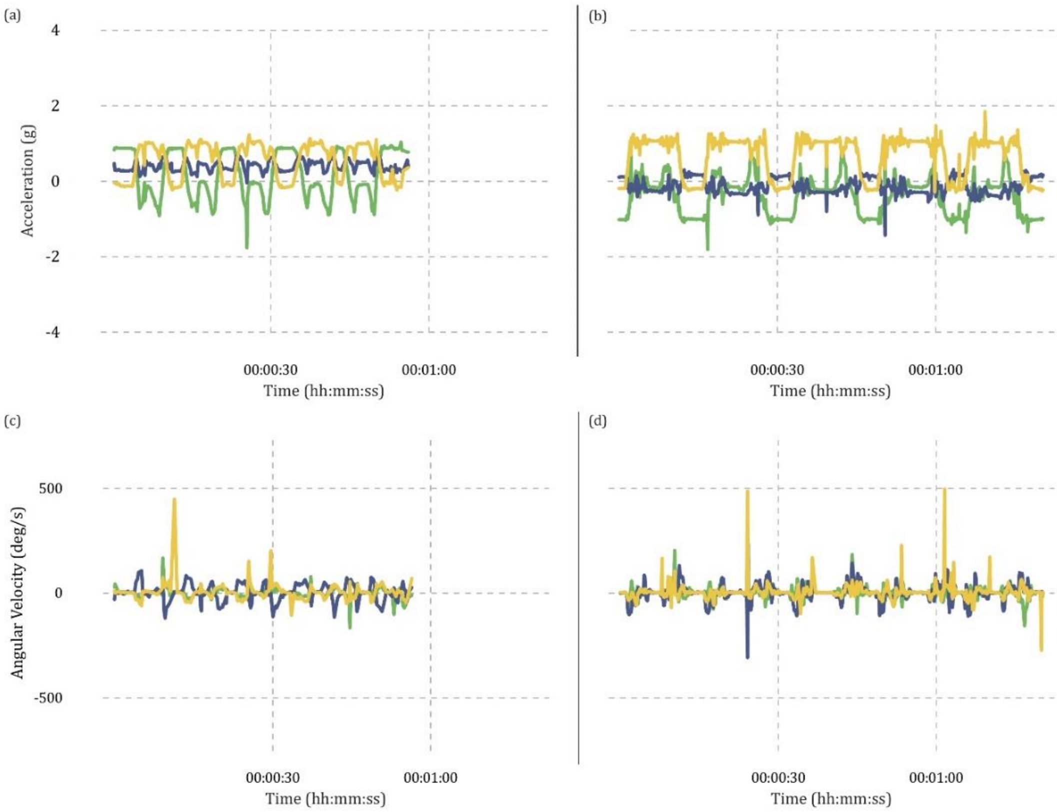

Figure A.31 Data taken at the thigh using the MetaTracker for lying down. (a) Acceleration data from the user trials, (b)Acceleration data from the validation trial, (c) Gyroscope data from the user trial and (d) Gyroscope data from the validation trial. x-axis, y-axis and z-axis.

Figure A.31 showed the lying down activity at the thigh. Like with the other validation experiments at the thigh, the pattern was observed to be the same, yet there are larger changes in the acceleration in all three axes.

A.4.3.5.1 25Hz

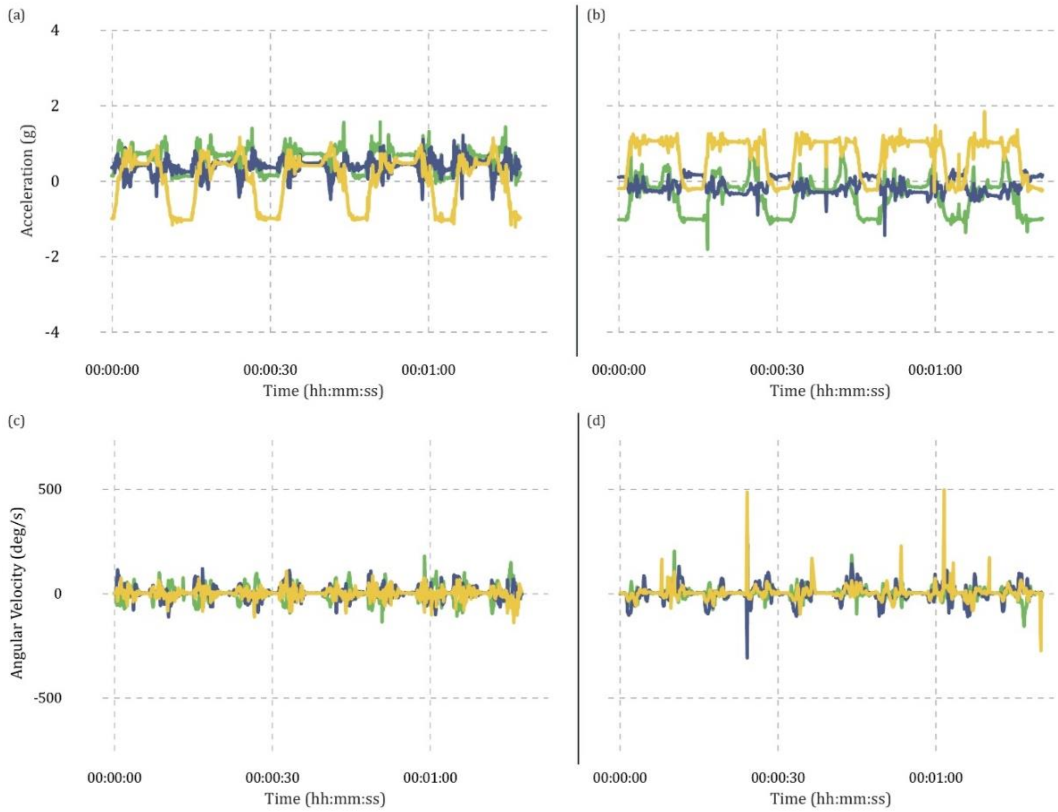

Figure A.32 Data was collected using a 25Hz sampling rate at the thigh for lying down. (a) Acceleration data taken using the Bosch system, (b) Acceleration data taken using the MetaTracker, (c) Gyroscope data taken using the Bosch system (d) Gyroscope data taken using the MetaTracker. x-axis, y-axis and z-axis.

The data recorded from both the MetaTracker and the Bosch sensors showed similar patterns. It was clear that the Bosch system was recording with the correct sampling rate. Also, it was noticed that there were fewer random outlier points in the data recorded with the Bosch system.

A.4.3.5.2 50Hz

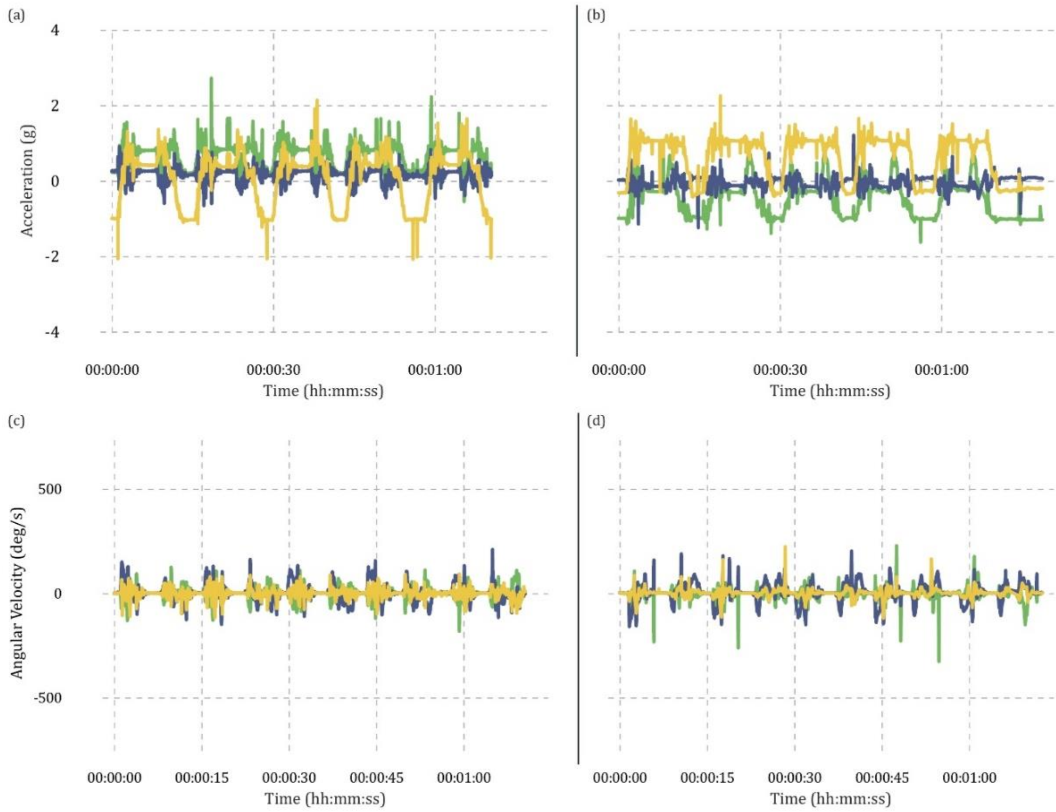

Figure A.33 Data was collected using a 50Hz sampling rate at the thigh for lying down. (a) Acceleration data taken using the Bosch system, (b) Acceleration data taken using the MetaTracker, (c) Gyroscope data taken using the Bosch system (d) Gyroscope data taken using the MetaTracker. x-axis, y-axis and z-axis.

Figure A.33 showed both Bosch and MetaTracker have the same pattern but larger changes in acceleration were observed for the Bosch. Additionally, when the participant was still there were large, seemingly random, changes in the acceleration when using the Bosch sensor system.

A.4.3.5.3 100Hz

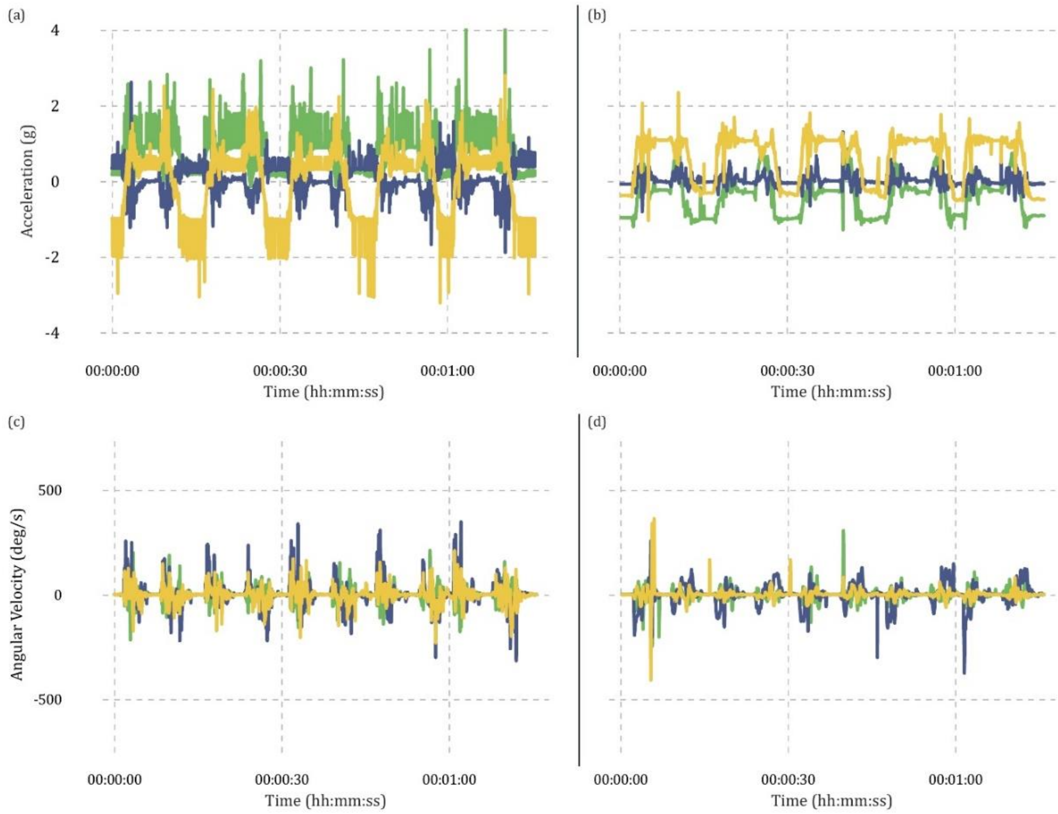

Figure A.34 Data was collected using a 100Hz sampling rate at the thigh for lying down. (a) Acceleration data taken using the Bosch system, (b) Acceleration data taken using the MetaTracker, (c) Gyroscope data taken using the Bosch system (d) Gyroscope data taken using the MetaTracker. x-axis, y-axis and z-axis.

Figure A.34 showed many more points were measured for the Bosch system which resulted in larger changes in the acceleration while the participant was still. This is because the Bosch system used a 100Hz sampling rate, yet the MetaTracker system was unable to collect at that rate. Otherwise, the pattern was the same for both kits.

B. Chapter 4

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Nottingham Trent University Schools of Art and Design, Arts and Humanities and Architecture, Design and the Built Environment Research Ethics Committee of Nottingham Trent University (protocol code 2021/22-28 and date of approval 17/12/2021).

B.1 Consent Form

CONSENT FORM: Garments for Healthy Ageing

Please read and confirm your consent to participating in this project by ticking the appropriate boxes and signing and dating this form. Digital Signatures are accepted.

1. I have read the project description and had the opportunity to ask questions about the project and these have been answered satisfactorily. ☐
2. I understand that my participation is voluntary and that I am free to withdraw by informing the researcher of this decision up to 14 days after the interview without giving any reason and without any negative implications. ☐
3. I give permission for the interview to be audio/video recorded. ☐
4. I undertand that the recording will be treated confidentially, anonymised and transcribed into text before being destroyed securely. ☐
5. I understand that quotations from the interview or responses given in writing, which will be made anonymous, may be included in material published from this research. ☐
6. I understand that any photographs I share may be included in material published from this research, but only where no individual is personally identifiable in the image. ☐
7. I am willing to participate in an interview as part of this research project. ☐
8. I understand that the anonymised data from this study may be used by those conducting subsequent studies, but only in its anonymised form in which I am not identifiable. ☐

____________________ _______________ ________________________

Participant's name Date Signature

____________________ _______________ ________________________

Researcher's name Date Signature

B.2 Participant Information Sheet

Garments for Healthy Ageing

Participant Information Sheet

1. Invitation and Purpose We are inviting you to take part in a research study investigating attitudes, habits and preferences of people 65-plus in relation to clothing and technology, particularly wearable technology. The information provided will be used to inform the research and development of 'wearable' medical, assistive and monitoring devices by the Advanced Textiles Research Group (ATRG) at Nottingham Trent University (NTU). Please read the following information carefully before you decide whether or not to take part.

2. Legal Basis for Research Studies The University undertakes research as part of its function for the community under its legal status. Data protection allows us to use personal data for research with appropriate safeguards in place under the legal basis of public tasks that are in the public interest.

All University research is reviewed to ensure that participants are treated appropriately and their rights respected. This study has been approved by NTU's College of Art, Architecture, Design and Humanities (CAADH) Research Ethics Committee.

Further information can be found at: https://www.ntu.ac.uk/research/research-environment-and-governance/governance-and-integrity

3. Why have I been asked to participate? You have been approached about this study because we are seeking to understand people's needs and experience to better design 'wearable' medical, assistive and monitoring devices.

4. Do I have to take part? Taking part in this research is voluntary. If you would prefer not to take part, you do not have to give any reason. If you change your mind you should contact Rachael Wickenden (details below) up to 14 days after the interview date. After this period you can still request for your contact details and any identifiable data to be destroyed, but anonymised research data will be retained.

5. What will taking part involve? The interviews will take place online or in-person at NTU in January and February 2022. Interviews should last between 30 and 45 minutes. We will ask questions about dress habits, garment preferences and wearable, assistive and monitoring technology. The interview schedule is provided for your reassurance, consulting the interview schedule beforehand is optional. You are not required to prepare for the interview, other than being ready to describe, show and/or share images of a favourite regularly worn garment and explain your preference.

There will also be a 30 minute follow up interview between May and June 2022, where the research team will share the prototypes developed to gain your feedback.

6. What are the possible disadvantages and risks of taking part? We do not anticipate that there are any risks in taking part. You will not be under any pressure to answer questions or talk about topics that you would prefer not to discuss and you can choose to halt or withdraw from the interview at any point. We explain how we will use the information you provide and how we will protect your personal information and confidentiality below.

7. What are the possible benefits of taking part? There are no direct benefits of taking part, although some people enjoy the opportunity to share their experiences.

8. How will my confidentiality be protected? We prefer to record the interview, with your consent. This allows us to accurately reflect what is said. The recording will be transcribed (written out) with any names or identifying information removed. The interview recording will be destroyed as soon as I (Rachael Wickenden) have a quality assured anonymous transcript.

Data will be stored on NTU secure servers and only members of the research team will have access to recordings, transcripts and observation notes during the project using their NTU login details.

Any quotes or data that we use will be anonymised, which means that they cannot be linked to you in subsequent research publications. Confidentiality will only be broken in circumstances where the researcher is concerned that there is a risk of harm to you or someone else. In this instance, the researcher must report this information to the relevant agency that can provide assistance.

9. What will happen to my data during the study and once the study is over? NTU will be responsible for all of the data during the study. Once the study is over, interview / video / audio recordings / personal information about you: such as your name and contact details, and the pseudonym key that allows anonymous data to be linked to participants will be destroyed. We will only keep the anonymised research data that would allow other researchers to check and verify our findings. This data will be deposited in the NTU data archive and will be preserved for ten years. Any data which could not lead to your identification, including analysed data and anonymised interview transcripts, will be made available via the NTU data archive on request. This controlled access will allow others (including researchers, businesses, governments, charities and the general public) to use the anonymised data, providing they credit the University and research team as the original creators. If you could potentially be identified through any information, only approved researchers will have access to this data for the purposes of ethically approved research. They will be required, ethically and legally, to work to protect your identity.

10. How will the data be used? We will use data from your interview to inform the design of prototypes, our final reports, journal articles and presentations – which will be publicly available. If you are interested, copies of any resulting publications can be made available.

11. Who can I contact if I have any questions or concerns about the study?

General Inquiries:

Lead researcher: Dr Rachael Wickenden, School of Art & Design, NTU,

rachael.wickenden@ntu.ac.uk

You should contact the Data Protection Officer if:

- you have a query about how your data is used by the University
- you would like to report a data security breach (e.g. if you think your personal data has been lost or disclosed inappropriately)
- you would like to complain about how the University has used your personal data

Email: jane.bonnell@ntu.ac.uk
Telephone: +44 115 84 83221

You should contact the Chair of the College of Art, Architecture Design and Humanities (CAADH) Research Ethics Committee if:

- you have concerns with how the research was undertaken or how you were treated

Email: amy-twigger.holroyd@ntu.ac.uk
Telephone: +44 115 84 88249

B.3 Interview Schedule

INTERVIEW SCHEDULE:
• Thank you for agreeing to participate in this research and for returning your consent form. The aim of this pilot project is to investigate attitudes, habits and preferences in relation to clothing of people 65-plus to inform the development of 'wearable' medical, assistive and monitoring devices by the Advanced Textiles Research Group (ATRG) at Nottingham Trent University (NTU). There are no 'right' answers to the questions, I am interested to hear your experience and your opinions. I may ask questions not on the interview schedule to gain a better understanding of your answers. • In line with consent, if you wish to withdraw from this interview at any point, you are welcome to do so. • Can you confirm that you are happy for this interview to be recorded? • I'd just like to remind you that the audio recording of this interview will be transcribed and anonymised so that you will not be identifiable from the resulting data. • The interview will take between 30 and 45 minutes. • Do you have any other questions before we go ahead?
Personal information
Age:
Clothing preferences
1. Have you brought or have in mind an example of a favourite regularly worn garment? 2. Could you talk about this item and explain why you chose it? 3. What are your priorities when choosing clothes to buy? 4. What are your priorities when choosing clothes to wear? 5. Could you describe any difficulties you may have putting on and/or taking off any items of clothing? 6. Do you experience any other difficulties relating to clothing i.e. availability, quality, washability, fit, comfort, style? 7. How do you feel about tight-fitting clothing, please consider different areas of the body in your answer? 8. How do you feel about stretch fitted garments such as thermal wear, cycling shorts or leggings? 9. Have you ever worn a compression garment, including socks or stockings, and if so, what was your experience of it/them i.e. comfort, stayed in place, ease of putting on / taking off?
Current and future health needs for yourself or someone else
10. Are there any current or possible future health needs relating you wish could be addressed using something you would wear?

Attitude to technology, wearable medical, assistive and monitoring devices
11. How would you describe your general attitude to technology? 12. In your own words, could you describe wearable technology? 13. Are you familiar with the term Electronic or E-textiles and if so, could you describe your understanding of them? 14. Do you wear a watch? 15. Do you own/use any form of wearable technology? 16. Do you own/use any form of assistive or health related technology? 17. Imagining an item of technology that needed to be worn regularly, where would you want that item to be positioned on the body? 18. Is there anywhere on the body you would not want wearable technology to be placed? 19. What weight and bulk do you consider acceptable for an item of wearable technology? 20. How do you feel about wearable technology being visible or concealed? 21. Would you want an item of wearable technology to be part of a specific garment or attachable to an item of clothing? 22. How would you envision interacting with an item of wearable technology? (computer, phone, device itself)
Fall prevention and detection
23. Do you have any issues relating to stability, mobility or movement? 24. Is the prospect of a fall something that concerns you and if so, how would you want to address that concern? A near fall is an event in which a person feels a fall is imminent but avoids it by compensatory action, such as grabbing a nearby object or controlling the fall. 25. Would you consider wearing a device that allowed you monitor your manner of walking aimed at detecting near falls and changes in stability? Why or why not? 26. Would you consider wearing something that allowed you to call for assistance? Why or why not? 27. How do you feel about a monitoring device for near fall detection positioned on the thigh, ankle or waist?
Clothing, wearable technology and society
28. Is there anything you would like to add or suggest relating to wearable technology and clothing for older adults?

B.4 Questionnaire

Ankle prototype - please rate the following on a scale of 1-5 (1=negative, 5=positive)	
Comfort	
Ease of use	
Practicality	
Durability	
Sustainability	
Appearance	
Materials	
Features	
Feel	
Overall design	
Please explain your evaluation and suggest improvements	

Shorts prototype - please rate the following on a scale of 1-5 (1=negative, 5=positive)	
Comfort	
Ease of use	
Practicality	
Durability	
Sustainability	
Appearance	
Materials	
Features	
Feel	
Overall design	
Please explain your evaluation and suggest improvements	

Patch prototype - please rate the following on a scale of 1-5 (1=negative, 5=positive)	
Comfort	
Ease of use	
Practicality	
Durability	
Sustainability	
Appearance	
Materials	
Features	
Feel	
Overall design	
Please explain your evaluation and suggest improvements	

Please rate the prototypes in order of preference from 1-3 (1=worst, 3=best)	
Ankle prototype	
Shorts prototype	
Patch prototype	
Please explain the order in which you have placed the prototypes	

C. CHAPTER 5

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Nottingham Trent University Schools of Art and Design, Arts and Humanities and Architecture, Design and the Built Environment Research Ethics Committee of Nottingham Trent University (protocol code 2022/23-09 (amendment to 2019/20-46) and date of approval 28/09/2022).

C.1 CONSENT FORM

CONSENT FORM PROFORMA

Dear Research Participant,

The population of the world is ageing, and it is creating a significant impact on the health and social care systems. Ageing is linked with frailty and a major risk factor of this is falling. Near falls are a precursor to falling and occur more often. Therefore, the ability to remotely monitor near falls and falls will help prevent injury and therefore will reduce pressure on hospitals and care homes. Wearable technology provides a solution to remotely monitor falls and near falls in real-time and non-invasively. The purpose of this study is to develop wearable technology, in the form of electronic textiles, for fall and near fall detection.

All participation in the project is voluntary. If you do you agree to be part of this project, we would like to use the information to develop reports, a thesis, presentations, and publications; but your name and identity will remain anonymous. All recordings will be stored securely and remain confidential. If you decide at any stage, you no longer want to be part of the project, just let us know within two weeks and we will make sure any information you have given us is destroyed.

This project has been reviewed by, and received ethics clearance through, the Nottingham Trent University College of Art, Architecture, Design and Humanities Research Ethics Committee

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Please read and agree to the following statements:

I have read the above project description and had an opportunity to ask questions about the research and received satisfactory answers to any questions.
I have had sufficient information to decide whether or not I wish to take part in the study.
I understand that I am free to withdraw from the research within two weeks by informing the researcher of this decision.
I understand that my personal information will be treated in the strictest confidence.
I understand that the results of the experiments will be included in in material published from this research.
I am willing to partake in the various activities required for this research project.
I agree to have video recordings made during this study and understand that the anonymised versions these recordings made publicly available.
I understand that anonymized data, which cannot identify me, will be publicly available in line with the University Research Data Management Policy.

Full Name ____________________________________

Date ____________________________________

If you have any questions please contact ……………………………..

C.2 Participant Information Sheet

NOTTINGHAM TRENT UNIVERSITY
Proforma: Research Consent Information Sheet

Protocol Title	Near fall detection using wearable sensors and electronic textiles
Principal Investigator	Zahra Rahemtulla
Project Group	Advanced Textiles Research Group
Supported By	Professor Jake Kaner

What is the purpose of this study?

The overall aim of this study is to develop technology for near fall detection using electronic textiles. More specifically the best sensor or combinations of sensors, as well as the correct location for the(se) sensor(s) on the body need to be determined so that the differences between a fall, a near fall and activities of daily living (ADLs) can be distinguished.

What are we asking you to do?

We would like you to walk around the lab and to perform various exercises wearing multiple sensors that are placed on different locations of your body. Some of these will be commercially available sensors, and some might be electronic textiles. At the same time, we will be video recording your movements as a validation of the technology.

The activities that we will ask you to perform are: walking, sitting on a chair, timed up and go test (standing from seated, walking and returning to seated), a controlled stumble and three types of falls onto a crash mat, you will be asked if you are comfortable to do this before the study.

We will be taking your pulse rate, pulse rate variability and temperature during the experiment, as well as data about your movement. As well as taking these physiological measurements we will need height and weight measurements, to record where the sensors were placed, and to ask you about the comfort of the sensors. Additionally, we will need to record your age and gender.

How we would like to use the information provided

The data that we collect will be used to determine the most suitable sensor(s) and the ideal placement of the sensor(s). Additionally, we will use the data to distinguish the differences between a fall, a near fall, and activities of daily living (ADLs).

Compliance with the Research Data Management Policy

Nottingham Trent University is committed to respecting the ethical codes of conduct of the United Kingdom Research Councils (RCUK) and EU GDPR. Thus, in accordance with procedures for transparency and scientific verification, the University will conserve all information and data collected during the experiments in line with University Policy, consistent with both RCUK, and the EU GDPR, (https://www.ukri.org/about-us/policies-and-standards/gdpr-and-research-an-overview-for-researchers/).

All data will be anonymised and, with your consent, made publicly available for anybody (including researchers, businesses, governments, charities, and the general public) to use.

Your participation does not involve any risks other than what you would encounter in daily life. If you are uncomfortable with any of the questions or activities you are free to not answer or participate.
What are my rights as a research participant?
Your participation in this project is entirely voluntary: • You have the right to withdraw your consent and participation at any moment: before, during, or after up to a period of two weeks. If you do wish to withdraw your consent please e-mail me at n0842040@ntu.ac.uk • You have the right to remain anonymous in any write-up (published or not) of the information generated during this study. • You have the right to refuse to answer to any or all of the questions you will be asked. You also have the right to specify which exercises you are willing to perform. • You have the opportunity to ask questions about this research and these should be answered to your satisfaction. If you want to speak with someone who is not directly involved in this research, or if you have questions about your rights as a research subject, contact Professor Michael White, Chair for the College Research Ethics Committee (CREC) for the College of Art Architecture Design and Humanities (CAADH) at Nottingham Trent University. You can call him at 0115 848 2069 or send an e-mail to michael.white@ntu.ac.uk.
What about my Confidentiality and Privacy Rights?
Unless required by law, only the study investigator and members of NTU staff have the authority to review your records. They are required to maintain confidentiality regarding your identity. Results of this study may be used for teaching, research, publications, and presentations at professional meetings. If your individual results are discussed, then a code number or a pseudonym will be used to protect your identity.
Audio/visual recordings
Any recorded data will be kept confidential and in a secure place in line with the Research Data Management Policy and destroyed in line with the current RCUK/University/GDPR Guidelines. Any of the recorded data and images will be taken by avoiding the face and where this is not possible the face will be blurred.
Who should I call if I have questions or concerns about this research study?
Professor Jake Kaner