Long-Term Activity Monitoring using Wearable Sensors Mounted in Loose Clothing

by

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Abstract

Using multiple Inertial Measurement Units (IMU) in movement analysis will not only be useful in increasing the classification accuracy of the movement data, but also reduce the computational complexity in classification algorithms as there is no need to process an increased number of features generated from a single sensor. However, wearing sensor devices every day on the same place with the same orientation is a key requirement for the data analysis purpose. To facilitate this, sensor devices can be mounted into clothing, as it is an ideal platform to cater these miniature devices. There are research studies conducted with sensors mounted into clothing such as smart garments, tight-fitting clothing and loose clothing (everyday wear clothing). Data validations are available between tight-fitting clothing-mounted sensor data and body-mounted sensor data, focusing mainly on limited set of activities or sensors.

The main focus of this research was to investigate the possibility of using loose clothing-mounted sensors in monitoring human movement patterns in a home based healthcare monitoring system, while validating how the loose clothing-mounted sensor data correlate with body-mounted sensor data with respect to different activities. In order to quantify and understand human movements in this research, time synchronised wearable sensors were mounted into loose clothing. This whole research was based on three datasets and they were used to conduct four sub analyses based on different types of human movement patterns to achieve the main goal. First analysis was based on data collected from Actigraph sensors from both body and clothing and the sensors were near waist, thigh and ankle/ lower-shank. This study validated the data between clothing and body mounted sensor data across various static and dynamic activities with respect to each sensor pairs. These validations were based on correlation coefficient values with respect to the accelerometer data pairs for different activities i.e. 'standing', 'sitting', 'sitting on a bus', 'walking' and 'running'. Promising correlations were observed (especially with static activities) with this dataset and the second dataset was collected from body and clothing-mounted lightweight IMU sensors. These data were analysed based on correlation coefficient values with respect to the inclination angle changes over 'gait' cycles. In addition to the correlation coefficient values, the data were analysed using different types of plots such as phase portraits and 3D plots. From these plots, it was noted that important features such as Mid-Stance (MS), Initial Contact (IC) and Toe Off (TO) points can be recognised by clothing data and they can be used to analyse 'walking' data in detail. Moreover, the third semi-natural dataset was collected from clothing-mounted sensors to check whether they can be used to implement posture and activity classifiers. These classifiers that were based on both Machine Learning (ML) and Deep Learning (DL) approaches with relevant selected features, also showed reasonably high classification accuracies. By taking into account all these promising observations, this thesis can be concluded that loose clothing-mounted sensor data can be used productively in movement analysis.

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Udeni Jayasinghe Kankani Pathirage

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List of Acronyms

ADL	Activities in Daily Life.
COTS	Commercial Off The Shelf.
DCM	Direction Cosine Matrix.
DL	Deep Learning.
GPS	Global Positioning System.
GRF	Ground Reaction Force.
HAR	Human Activity Recognition.
HC	Healthy Control.
HY	Hoehn and Yahr.
IC	Initial Contact.
ICC	Intra-class Correlation Coefficient.
IMU	Inertial Measurement Units.
KNN	K-nearest neighbour.
LSTM	Long Short-Term Memory.

MARG	Magnetometer Angular Rate & Gravity.
ML	Machine Learning.
MS	Mid-Stance.
OECD	Organisation for Economic Co-operation and Development.
PwP	Patients with Parkinson's.
RCD	Remote Care Delivery.
SVA	Sensor to Vertical Angle.
TO	Toe Off.
UPDRS	Unified Parkinson's Disease Rating Scale.

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Chapter 1

Introduction

As wearable sensors have become smaller, more lightweight with reduced power consumption and increased accuracy, the popularity of these sensors has increased, particularly in their usage in wearable devices [1, 2]. Especially, the usage of wearable Commercial Off The Shelf (COTS) sensors have become popular nowadays because these devices, that are being widely used in healthcare and sports sectors, are capable of monitoring day-to-day activities [3, 4, 5]. As such, it can be anticipated that long-term activity monitoring systems in hospitals could also be replaced by wearable sensor devices [6, 7]. Then, it would be a solution to two main problems in the healthcare sector. Firstly, it could help in reducing the annual cost which is allocated for long-term health monitoring as it is considered to be a larger amount [8, 9]. Secondly, the other thing is, the sensor readings could be used in diagnosing patients like *Patients with Parkinson's (PwP)* as clinicians have no other clinical criteria for analysing the health condition of such patients. The severity of the PwP is assessed by using rating scales such as the Unified Parkinson's Disease Rating Scale (UPDRS) and Hoehn and Yahr (HY) rating scale [10, 11, 12, 13] depending on patients' verbal descriptions.

1.1 Motivation

In many countries the ageing population is increasing annually. The population over 60 years from 2015 and 2030 is projected to increase by 23.1% in Europe and by 40.5% and 70.6% in Northern and Latin America respectively. In Asia it is expected to increase by 66.3% and 63.5% in Africa [14]. When comparing the data between 2015 to 2030 with the countries' income rate (i.e. high income, middle income, low income), the percentage of older adult population is projected to increase rapidly by 2030 in high and middle income countries while that low income countries projected to have a slightly low increment compared to the other countries [15]. Healthcare systems in each country must be able to cater to these increasing number of older adults' needs [14] and there is a high demand for care dependency in each country with the increment of the older population [15]. Even in Organisation for Economic Co-operation and Development (OECD) countries have seen an annual increment of 4.8% of the cost allocated for long-term monitoring from 2005 to 2011 and also it is predicted that the cost as at 2015 would be doubled by 2060 [16].

As a solution for the increasing cost that has to be allocated for long-term health-care, the usage of assistive technology has been introduced as a cost effective long term monitoring model instead of care dependence of adults [17]. A study done by Global coalition on aging [18] has proven some instances where Remote Care Delivery (RCD) (such as video conferencing with healthcare providers, tablet-based patient education, software applications which are tracking diet, exercise and medication) helped to reduce the heart failure patients' hospitalization rate by 40% in 2018 in the UK. Other than the above mentioned assistive technologies, there are many other facilities that are being used in uplifting the older adults quality of life, such as electronic sensors usage to identify smoke and heat and to switch on lights when it is dawn/dusk, video-monitoring, pressure mats, speaking clocks, portable devices to manipulate some items remotely in addition to simple techniques like having grab rails, walking frames and doorbell amplifiers [19]. In recent years the usage and popularity of wearable devices have risen substantially [20] and it is predicted to increase at a compound annual growth rate of 38.8% from 2017 to 2025 [1].

Activities in Daily Life (ADL) are fundamental properties that are considered when enhancing senior citizens'/ patients' quality of life of under the domain of healthcare systems. The five main ADL are personal hygiene, dressing, eating, maintenance of continence and mobility[2]. The main target is to monitor the fine movements while assuring that the patient can do his/her work independently. Yet, above all, mobility plays a major role in ADL [21] and often more priority is given to analyse human movement patterns.

Wearable sensors can be used in healthcare systems in various aspects such as in rehabilitation, monitoring the fine movements of the patients who suffer from chronic diseases like Parkinson's or Dementia, real time monitoring of heart failure patients, falls detection and sports medicine. The usage of sensors in long-term monitoring in patients has benefits in various aspects in addition to cost effectiveness. The patients who are unable to travel frequently, do not need to visit the clinicians frequently if the clinicians can access the data files of the patients and analyse their behavior even without seeing them. The other benefit is that when the diagnosis is based on patients' own verbal descriptions where there are no clinical criteria to measure diseases like Parkinson's, the clinicians would be able to rely on the sensor data which is more reliable than the patients' diaries.

1.1.1 The Use of Wearable Sensors in Five Main Sectors

Grand View Research Report[1] categorised the wearable sensors into 5 sectors i.e. Consumer, Defense, Healthcare, Industrial and Other. The global sensor market-

[1] Research, Grand View. 2018. "Wearable Sensors Market Size, Share & Trends Analysis Report By Sensor Type, By Device (Smart Watch, Fitness Band, Smart Glasses, Smart Fabric), By Vertical, By Region, And Segment Forecast, 2018 - 2025. "https://www.grandviewresearch.com/industry-analysis/global-wearable-sensor-market"

[2] Paying for senior Care. "What Are the Activities in Daily Life (ADL)",2018. https://www.payingforseniorcare.com/longtermcare/activities-of-daily-living.html

share for each category in the year 2016 is depicted in Figure 1.1.

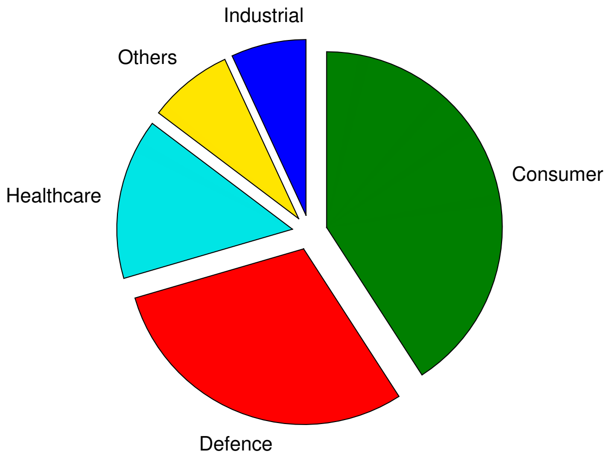

Figure 1.1: Global wearable sensor market demand in 2016 under each category [1]

By looking at Figure 1.1, it can be said that after the high demands in consumer (mobile phones, cameras, gaming devices and media players) and defense sectors (surveillance, navigation, weapons-locating systems, tracking a soldier's location and vitals, chemical detection, sensing the quality of food and water, camera sensors, infrared sensors and sensors in Aerospace Applications), sensors are being most highly used in the healthcare sector. These wearable sensors can be used in healthcare systems not only in long term monitoring, but also in real time monitoring. IMU continue to dominate when compared with other sensors [22]. The sensors that are used in fitness, entertainment, gaming, in animal tracking and monitoring fall under the 'Other' category in Figure 1.1.

In addition, the Grand View Research Report[1] also has analysed the way of increasing the market size depending on each sensor type such as accelerometer, gyroscope, magnetometer, inertial sensor, heart rate monitors, temperature sensors and sleep monitoring sensors. They have predicted that the market size will be increasing highly from 2014 to 2025 and the main reason for this growth is the rapid usage of sensors in health and fitness monitoring systems [1].

1.1.2 Importance of Wearable Sensor Devices in the Healthcare Sector

Wearable sensor devices can be defined as electronic devices that can be worn in such a way that they are able to monitor and record the corresponding activity data in an unobtrusive way [23]. People use commercially available wearable devices such as smart watches, fitness bands, smart glasses, smart fabric, smart footwear and smart rings to maintain a healthy life style or to self-monitor their fitness levels [24, 25]. Most of these devices are used to track human motion and they can be used in sectors like health and sports. For example there are wrist bands and watches that can be used as activity trackers (based on step counting, daily calorie intake, sleep and wake up patterns), sport watches (based on Global Positioning System (GPS), heart rate monitor and swimming), running watches (log running), and smart watches [24, 25]. These devices come under various famous brands such as Garmin[3], Fitbit[4], Misfit[5], Apple fitness products [6] and Actiwatch[7] [24, 26]. These devices can be used to monitor the daily workout and can give an insight into monthly or daily workout targets easily without manually entering data. However, usually people wear a single device from each wearable type, at a time, hence, these devices might not be able to provide an accurate picture of the wearer with the limited set of data [27]. For example, most of the wearable devices come as wrist bands with triaxial accelerometers and algorithms that are designed to classify the motion patterns calculating the step count and other movements. These motion patterns are categorised into activities based on the threshold values set up by the device. However, sometimes the activities may be misclassified when it detects some signals which are above or lower than the expected threshold values of the device. For example, at sometimes Fitbit devices overcount the steps when the wearer rides

[3] https://www.garmin.com/en-GB/
[4] https://www.fitbit.com/uk/home
[5] https://misfit.com/
[6] https://www.apple.com/uk/shop/watch/watch-accessories/health-fitness
[7] http://www.actigraphy.com/

on bumpy roads, at the same time, if the expected acceleration is not met with, it does not count the steps as required [8].

In order to improve algorithms and to mitigate these types of uncertainty, it is better to have multiple sensors on a single person, especially in medical applications where there is a need for reliable data in decision making. As in medical applications, the data should be able to be used in predictions, anomaly detection and diagnosis support.

Bao et al. [28] and Foerster et al. [29] have demonstrated how the activity recognition can be improved by using multiple sensors. As the usage of multiple sensors can improve the classifier performance, there exist a significant amount of research studies carried out with multiple sensors [30, 31, 32].

Usage of multiple sensors in activity/ posture recognition not only improves classification accuracy but also the efficiency of the algorithms. Gao et al. [33] explained that there is a trade-off between using a single wearable sensor data to extract a considerable amount of data on heuristic features that train complex classifiers and using multiple sensors with less number of features with light-weight algorithms.

Wearable sensors that are used in healthcare can be categorised into two main types, namely bio-mechanical sensors and physiological sensors. They can be further categorised into sub categories depending on the measurements of the sensors as shown in Table 1.1. Moreover, Table 1.1 indicates that all the kinematics related bio-mechanical sensors to be used in monitoring the human movements, can be mounted on or near the body.

[8] https://help.fitbit.com/articles/en_US/Help_article/1141

Bio-mechanical	On/Near Body	Transcutaneous
Kinetics		
Force [35]	✓(in shoes)	
	Insole force sensors	
Torque [35, 38]	✓(in shoes)	
	Insole torque sensors	
Kinematics		
Accelerometers [43, 44, 45]	✓	
	Limb acceleration	
Gyroscopes [43, 44, 45]	✓	
	Limb angular velocity	
Magnetometers [43, 44, 45]	✓	
	Limb orientation	
Energy Expenditure		
Various Movement Sensors [47, 48]	✓	

Physiological	On/Near Body	Skin	Transcutaneous	Implant
Blood Pressure[34]		✓ (On cuff)		
Blood Glucose [36]			✓	✓
Calorie Monitor [37]	✓	✓		
	Respired Oxygen / Accelerometer + Blood Pressure + Impedance sensors			
ECG Monitor [39, 40, 41]		✓		
	records the electrical activity generated by heart muscle depolarisations, which propagate in pulsating electrical waves towards the skin			
EEG Monitor [42]		✓		
	Records electrical activity in the brain using small, metal discs (electrodes) attached to your scalp			
Pulse Rate [46]		✓		
	Plethysmography concept: Heart rate in Beats per Minute using an optical LED light source and an LED light sensor. The light shines through your skin, and the sensor measures the amount of light that reflects back.			
Hydration Monitor [46]		✓	✓	
Pulse oximeter[36, 46]		✓		
	uses light to measure how much oxygen is in the blood			
Body Temperature [39, 46]		✓		
Galvanic Skin Response [46]		✓		
	Measures the continuous variations in the electrical characteristics of the skin			

Table 1.1: Wearable Sensors in Health Care

1.2 Problem Statement

It is hard to come to a proper conclusion regarding the movements based on data collected from a single limb. In order to make a proper analysis of the movement patterns of people in health applications, increasing the number of sensors/sensor fusion could be a better solution [28, 29]. Increasing the number of sensors would allow more data to be gathered and to facilitate a more comprehensive analysis. Hence, rather than depending on a single device, it is assumed that it would be beneficial to have multiple sensors on different places on the body.

Wearing the sensors on the same place on a daily basis, with the proper orientation, is crucial for the data analysis process and so the sensors need to be placed with special care. As suggested, strapping multiple sensor devices every day on the limbs of a patient/elderly person can be an additional burden or exacerbated to the carers or the patients themselves when the sensor design expects good dexterity from the wearers. Another shortcoming is the usage of the strapping bands because the sensors might have a tendency to move with respect to the limb owing to the non-rigid characteristic of the bands.

To make the process of wearing the sensors in a consistent location and orientation easier, one approach is to attach lightweight sensor devices to the clothing that people/patients wear every day [49, 50]. This benefits both the subject and the data analyser because the subject can wear multiple sensors in one or two attempt/(s) (sensors on top and sensors on trousers or skirts) and the data analyser can get a good picture of the activity taking into account the whole body of the subject. There exists research carried out with multiple body-mounted sensors [51, 52, 53] and clothing-mounted sensors [50, 54]. Most of the clothing mounted sensor based research were carried out with tight fitting garments as loose clothing might add additional movements to the sensors. However, tight fitting clothing are not comfortable to be worn for an extended period of time [55] especially when the purpose is to monitor movements in long-term healthcare systems. People who are in need of home-based long-term monitoring systems are either people with movement disorders or older adult people. Hence, using loose clothing that people wear everyday would be beneficial for these cohort of people instead of having to wear tight fitting clothing.

There are only a limited number of research studies in validating clothing-mounted sensor data. One such work validated the association between tight fitting clothing-mounted readings and body-mounted sensor readings with respect to a single activity (dead-lifting) [54] and another work proved that sensors attached onto fabric produced better signal variations that could be used with activity classification [56]. However, the second research collected data mimicking clothing-mounted sensor data by attaching sensors to three different fabric materials which were then attached to a pendulum [56].

As such, a systematic analysis needs to be carried out to assess, up to what extent these everyday wear clothing-mounted sensor data can be used in movement analysis systems and activity classifiers.

1.3 Research Question

This thesis aims to investigate the possibility of using loose clothing-mounted sensors in monitoring human movement patterns with a view to eventually using them in a home based healthcare monitoring system. For that, there should be a systematic validation between the clothing-mounted sensor data and body-mounted sensor data with respect to different daily activities and have to check whether the clothing data can reveal any movement related data.

In order to achieve these targets, this work addressed the following two main research questions.

1. How well does the clothing-mounted sensor data correlate with the body-mounted sensor data?

2. Is there a possibility of extracting enough information about human movement through the clothing-mounted sensor data?

1.4 Aims and Objectives

The broader aims of the research were to quantify and understand human movements over extended periods by using multiple clothing-mounted wearable sensor devices and to implement posture and activity classifiers with these data.

To achieve the above mentioned aims, five main objectives were identified and they are to:

1. quantify how strongly sensors mounted onto body and clothing correlate with each other depending on different activities and clothing types, by calculating correlation coefficient values of accelerometer data between signal pairs.

2. make publicly available a semi natural dataset collected from clothing-mounted lightweight IMUs for an extended period of time.

3. use the clothing-mounted lower body of the body sensor data in posture classification.

4. collect a supplementary dataset covering the lower body with 6-9 lightweight IMUs to quantify the correlation between body-mounted and clothing-mounted sensor data with respect to 'walking' data. Further to check whether there is a possibility of extracting useful information related to 'gait' from clothing data (lateral side of the clothing-mounted sensor data), similar to the frontal side of the body mounted sensor data as body-mounted sensors mount usually on

the frontal side of the body and it is convenient for the wearer to have sensors on the seam of clothing.

5. implement an activity classifier to classify activities such as walking, climbing up and down stairs and making turns based on clothing-mounted sensor data.

1.5 Contributions

The main contributions of this thesis are as follows.

1. Demonstrated that clothing-mounted sensors' performance were as acceptable as body-mounted sensors, across different types of activities (static postures and walking) using sensor pairs (clothing and body-mounted) mounted near waist, thigh and ankle/ lower-shank. This was done by analysing correlation coefficient values with respect to the accelerometer data and inclination angles estimated by using accelerometer, gyroscope and magnetometer data.

2. A dataset, collected from 6 clothing-mounted sensors covering the lower body along with the video ground truth data and diary data for semi natural activities. The dataset consisted of 15 participant-days worth of data collected from 5 participants (Even though the data were collected from 12 sensors, only the data collected from 6 sensors mounted on the lower body, were analysed in this research). To my knowledge this is the first published database consisting of data collected from loose clothing-mounted IMUs. This dataset is likely to be of interest to researchers studying human postures and movements in natural settings, particularly that the sensors are worn unobtrusively in loose-clothing rather than on the body and also that the data includes measurements of the waist, thigh and ankle on both the left and right sides.

3. A posture classifier with a high accuracy (100%), implemented by extracting a single feature from multiple sensors. The classifier was implemented based

on three clothing-mounted sensors (placed near waist, thigh and ankle/ lower shank) and used a single feature so that the computational intensity would be minimised and accuracy would be increased.

4. Demonstrated that a reasonable accuracy can be achieved in activity classification by using selected number of sensible features with DL approach rather than feeding all the raw data to train a network.

1.6 Outline of the Dissertation

This thesis is organised as a collection of papers. After this introduction in Chapter 1, Chapter 2 reviews the literature related to movement analysis by using wearable sensors, examining the optimal sensor placement in movement analysis, how multiple sensors can enhance the accuracy of classification, suitable data sampling rate to collect data, sensor orientation correction mechanisms, common features that can be used in Human Activity Recognition (HAR), and how sensor fusion could be used in classification and analyses based on clothing-mounted sensors.

This research mainly consists of one feasibility study and three main data analyses. Before collecting data for the main data analysis from loose clothing-mounted sensors, the feasibility of collecting data with clothing-mounted sensors were checked and scrutinized the data to check how well the clothing data correlated with body-mounted sensor data. To accomplish this, a single person study was carried out as a feasibility study with four to six Actigraph devices [7] (a commercially available sensor). These sensors were mounted onto different types of clothing (loose slacks, a pencil skirt and a knee length frock) covering lower body (waist, thigh and ankle) to collect data based on different types of activities (walking, running and sitting). Chapter 3 compares these clothing-mounted data with body-mounted sensor data based on correlation coefficient values correcting for time lags (time lag between body-mounted sensor reading and clothing-mounted sensor reading) in sensor pairs across all the activities and clothing types based on cross correlation of the signals. Further, this chapter analyses how well these data could be used in activity classification. Based on all the results, this chapter concludes that clothing-mounted sensor data were well correlated with body-mounted sensor data in slow activities compared to walking and running data. Also, this study suggests that the correlation and the accuracy of activity classifier could be improved by using lightweight sensors as Actigraph sensor weighs 19 g. This chapter covers objective 1 that is mentioned in Section 1.4.

As there was an insight that the accuracy could be enhanced in activity classification with lightweight sensors, this research collected data from 5 participants with lightweight sensors across 1-4 days for 5-8 hours. Chapter 4 describes a dataset of everyday activities collected from loose clothing mounted IMUs from lower body. The chapter describes the procedures followed in the main data collection, the preprocessing techniques and the usage of the dataset. This chapter addresses objective 2 of this research. The data collection procedure was reviewed by the research ethics committee of the School of Biological Sciences, University of Reading, UK and given a favourable ethical opinion for conduct (reference SBS 19- 20 31). The corresponding documents for ethical approval can be found under Appendices as Appendix A.1 and A.2.

Based on the chapter 3 results, it was noted that the clothing-mounted data were well correlated with body-mounted data in slow activities/postures, hence the data mentioned in chapter 4 were used in implementing a posture classifier while focusing on how different sizes of time windows could be used in feature extraction in different scenarios in training purposes. Further, posture classifier outputs were compared along with the diary data of the participants where there were no video ground truth data. Hence this chapter 5 accomplishes the third objective of the research. Supplementary material related to Chapter 5 can be found in Appendices as Appendix B.1-B.3.

Based on chapter 3 observations it was noted that the correlation between sensor pairs for activities like walking and running could be enhanced by using lightweight sensors. Hence, another six data sets were collected from 3 participants placing 6-9 sensors on lower body (on body and clothing) to examine 'walking' data. Chapter 6 analyses these body-mounted and clothing-mounted sensor pairs based on 'walking' data and examines what information could be extracted from clothing-mounted data by using phase portraits. This chapter 6 concludes that the clothing-mounted data correlate well with the body-mounted sensor data with respect to the 'walking' data. Objective 4 of the research is achieved by this chapter 6. Supplementary material related to Chapter 6 can be found in Appendices as Appendix C.1 and C.2.

Chapter 7 examines the feasibility of using clothing-mounted lower body data in classifying activities such as walking, climbing up stairs, climbing down stairs and turning. Heuristic and non-heuristic data were used in examining how well these data could be used in training activity classifiers based on both machine learning and deep learning approaches. Further, phase portraits for each activity were compared with respect to the angles each sensor makes in the sagittal plane with the vertical axis. Chapter 7 covers the fifth objective of the research. Supplementary material related to Chapter 7 can be found in Appendices as Appendix D.1.

Chapter 8 is a general discussion based on all the analyses conducted throughout this research based on clothing-mounted sensor data in movement analysis.

Finally, this dissertation concludes with Chapter 9 with the conclusions and possible future work that can be carried out based on this research.

The associations between the chapters are depicted in Figure 1.2. The datasets and chapters that depend on the conclusions of previous studies are marked in the same colour in Figure 1.2.

Chapter 3 and chapter 6 used separate datasets and they are coloured in orange and blue, while the other three chapters' 'data' columns are coloured in green to indicate that chapter 5 and chapter 7 used the data from chapter 4.

The conclusion that is highlighted in cyan gave the insight to chapter 4 and chapter 6. Chapter 5 was conducted based on the conclusion that is highlighted in yellow in chapter 3. Finally, chapter 7 was carried out upon a conclusion that was derived from chapter 6.

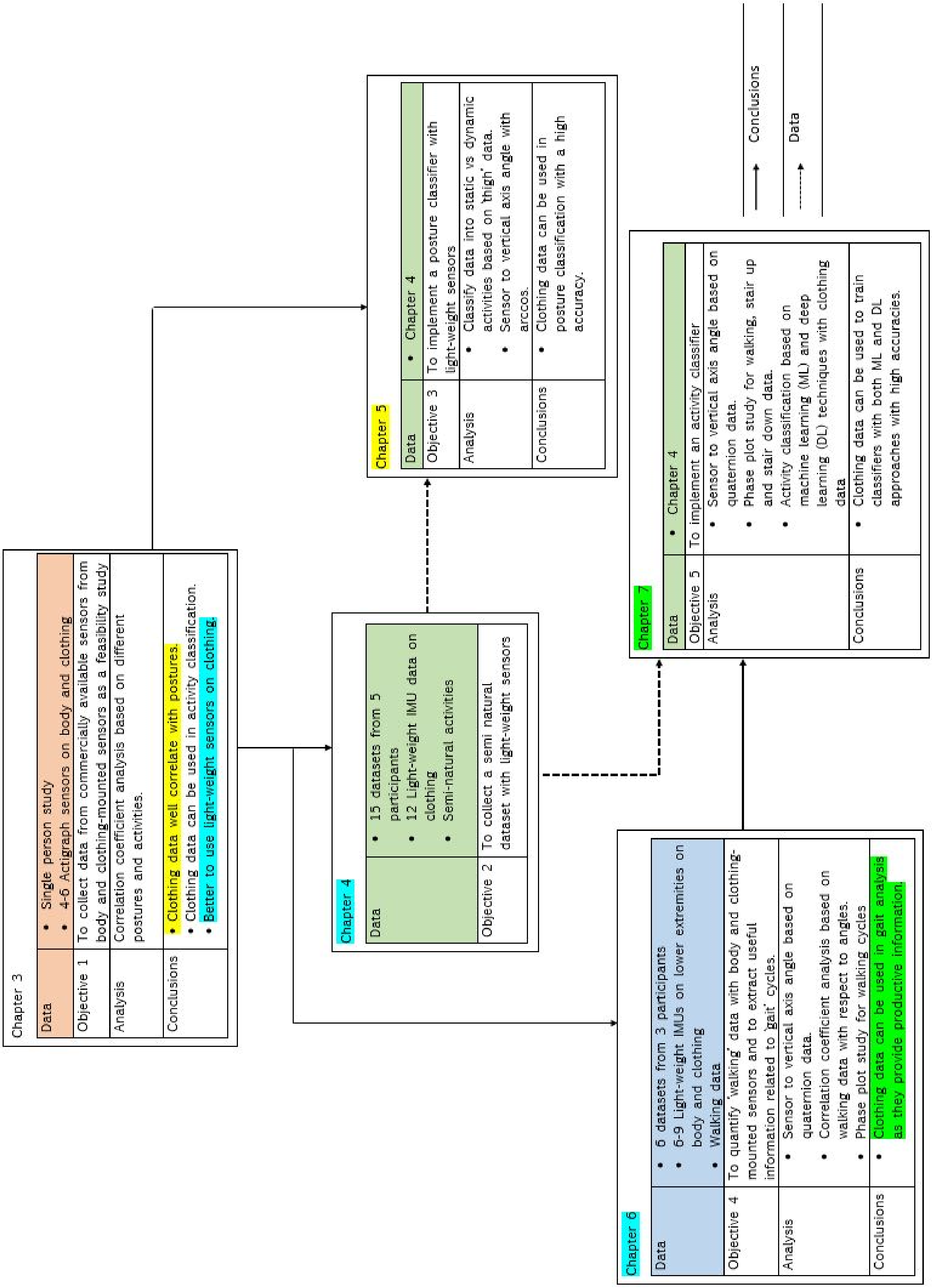

Figure 1.2: Associations between the chapters. Chapter 3 and chapter 6 used separate datasets and they are coloured in orange and blue, while the other three chapters' 'data' columns are coloured in green to indicate that chapter 5 and chapter 7 used the data from chapter 4.

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Chapter 2

Literature Review

2.1 Introduction

This literature review analyses previous work that supports the main research, focusing on long-term movement analysis with clothing-mounted multiple wearable sensors. The literature was mainly reviewed under seven areas i.e. to examine the optimal places to wear sensors to monitor movements, how multiple sensors can improve accuracy of classification, suitable data sampling rate to collect data, sensor orientation correction mechanisms, common features that can be used in activity recognition, sensor data fusion methods and clothing-mounted wearable sensor readings in activity monitoring. At the end of each section, there is a brief explanation how the previous literature is incorporated in this research.

There are various possible mechanisms that can be used in long-term movement monitoring, outside of clinical or laboratory settings. When proposing home-based monitoring systems, there are some factors to be considered with respect to reliability and security. These monitoring approaches should be reliable to measure real time data, safe to use with elderly people or patients who are having mobility issues and have the computational power to deal with the complexity of the algorithms in the programmes, the area covered by the monitoring system, the cost and the energy management [1].

These approaches can be categorised into 3 main groups i.e. non-wearable sensors, wearable sensors and hybrid systems that combines both wearable and non-wearable sensors [2]. These non-wearable sensor approaches are supported by image processing techniques and floor sensors [2]. Image processing techniques can apply to data capture from two types of sources i.e. analogue/digital cameras and other cameras that come with optic sensors (laser range scanners, time-of-flight) which can be again categorised into subgroups based on the usage of the markers [2].

Motion capture systems/ commercialized tracking systems and camera systems along with force plates are the most commonly used reliable movement/gait monitoring systems [3]. However these approaches are expensive, the monitorable area is confined to a limited area and the lighting conditions need to be maintained properly in order to get proper results [3].

For elderly people or patients who are under rehabilitation stages from movement difficulties or people who are suffering from chronic movement disorders, their homes are considered as their rehabilitation places [4]. Usage of sensor devices gives an opportunity to capture data on people's everyday activities more easily and in an economical way outside of clinical environments [2]. As this research focuses on collecting data from people for extended period of time, it was decided to use wearable sensors. However, both these wearable and non-wearable approaches have pros and cons of theirown.

Table 2.1 describes them with respect to long-term monitoring.

	Advantages	Disadvantages
Non-wearable approach	No restrictions in energy/power	Since these systems must have good lighting conditions without signal barriers, it is unable to be used in home-based environments
	No need to attach devices to the people	
	Capability of getting multiple measurements and complex analysis	Owing to the confined area, the normal behaviour cannot be captured
	Less interferences because of the confined space	Expensive
	Measurements can be controlled in real time	
	Track the real time movements and notify the carers	
Wearable approach	The ability of monitoring daily routine for a long time	Energy conservation is a major issue
	Cheaper than other systems	Susceptible to many external factors such as noises, frequencies etc.
	The ability of deployment in any sort of environment	Have to interpret data to get a meaningful idea based on the data
	The availability of various models and types of sensors	
	The patients have the autonomy to make decisions and do his/her activities	
	Wireless communication	

Table 2.1: Comparison of Wearable Systems with Non-Wearable Systems [2]

Potential unobtrusive sensor types that can be used in long-term monitoring are listed below [4].

- Biomechanical sensors
  - Accelerometer, Gyroscope, Magnetometer, Bed sensor, Scale, Pressure sensor, Vibration sensor
- Electro-magnetic
  - Contact sensor, Electrocardiography (ECG) sensor, Power meter, Radar
- Optical
  - PIR (Passive infrared) motion sensor, Infrared camera, Video camera, Depth camera
- Air-relevant
  - Gas/dust sensor, Humidity sensor, Thermometer
- Acoustic
  - Microphone, Ultrasonic sensor
- Unclassified
  - Water flow sensor, Computer monitoring (software), Phone monitor

The data collected from the above mentioned sensors can be analysed under three main topics i.e. physiology, behaviour and environment [4]. This research focuses on analysing behaviour patterns such as the time spent on activities, time spent on static postures and gait parameters. Hence, this research has used biomechanical sensors including accelerometer, gyroscope and magnetometer.

The next section discusses past research on how the sensor placement can be done in order to capture human body movements in an optimal way.

2.2 Optimal Places to Mount Sensors

Gemperle et al. [5] defined a set of design guidelines for implementing wearable sensors. The first guideline was based on sensor placement that needs an unobtrusive mechanism. They suggested that the most suitable areas for the sensors to be placed on the human body should be based on the following criteria:

1. areas that are approximately similar in size to every adult
2. areas that are resistant to movements while the body is moving
3. areas that have a larger surface area

Following the above mentioned criteria, Gemperle et al. [5] defined eight optimal areas to place sensors and they are collar area; rear upper arm; forearm; rear, side and front rib-cage; waist and hip;thigh; shin; top of the foot as shown in Figure 7.1.

Yang et al. [6] mentioned in their study that waist is considered as a better place to mount a sensor in gathering data about human movements as 'waist' is close to the center of the mass.

Montoye et al. [7] investigated how hip, thigh and wrists (left and right) mounted accelerometer data could be used in identifying the intensity of physical activities (PA) such as sedentary behaviour (lying down and sitting: reading and computer use), light intensity PA (standing, doing laundry, sweeping, biceps curls, slow walking) and moderate-to vigorous-intensity PA (fast walking, jogging, cycling, stair climbing and squats). They trained an artificial neural network (ANN) by using 10th, 25th, 50th, 75th, and 90th percentiles extracted from 30 second windows. Altogether they used 15 features ($= data from\ 3\ axes \times 5\ percentiles$) in the training process. Montoye et al. concluded their study observing more than 99% accuracy in identifying sedentary behaviour, light intensity PA and moderate-to vigorous-intensity PA with the thigh sensor [7]. Further, they observed that the non-dominant wrist data also

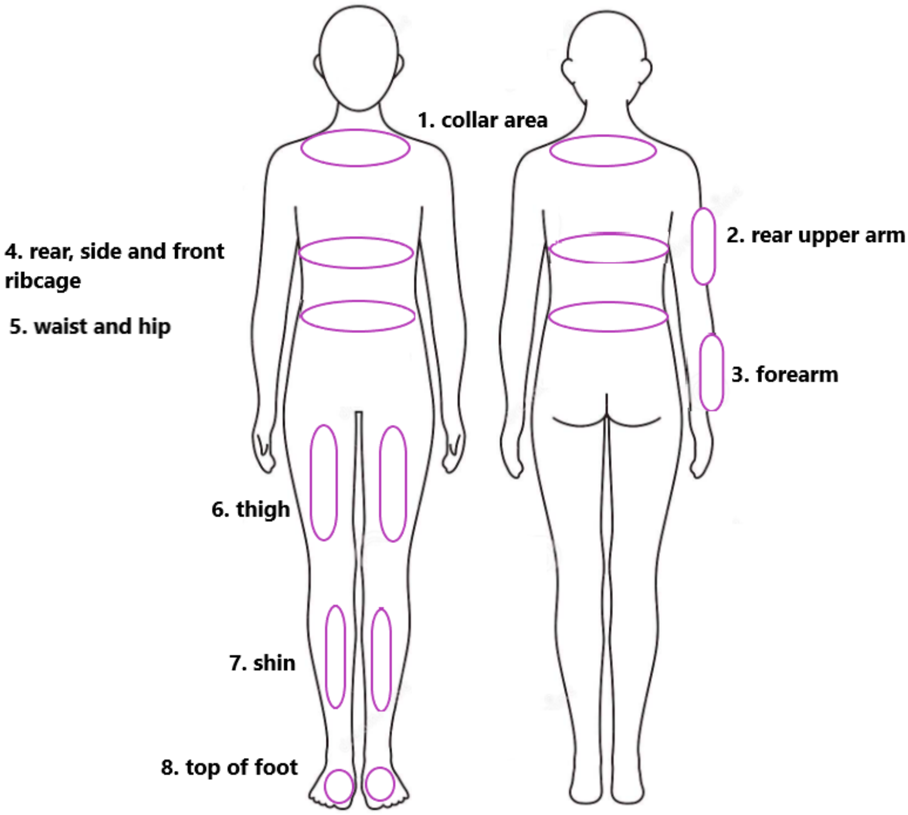

Figure 2.1: Unobtrusive places where wearable sensors can be mounted. [5]

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classified sedentary behaviour with high accuracy while having misclassifications in classifying light intensity PA and moderate PA. Moreover they observed that the non-dominant hand data was useful in PA classification compared to the dominant hand data. Finally, they mentioned that hip and dominant hand worn data classified the activities at the lowest accuracy.

On the contrary, Cleland et al. [8] claimed that the hip data showed the highest accuracy in their activity classifier compared to the other five sensor placements on lower back, wrist, foot, chest and thigh, and even higher than the accuracy that obtained by combining all the sensor data. They used heuristic features extracted from accelerometer data and energy based on fast Fourier Transformation values collected from Shimmer sensors [1]. They used decision trees (DT), Naïve Bayes (NB) and neural network for their classifiers based on Weka software [2] that is based

[1]https://shimmersensing.com/

[2] https://www.cs.waikato.ac.nz/ml/weka/

on Java language. Gjoreski et al. [9] used four accelerometers on chest, waist, thigh and ankle to detect postures (standing, sitting, lying down and sitting on the floor) and falls detection. Their conclusion was, to detect falls, chest or waist sensors could be used and they recommended a 'waist' sensor over a 'chest' sensor as it is easier to mount. They noticed a higher posture classification accuracy when combining a chest or waist sensor with an ankle sensor.

Lützner et al. [10] claimed that the different sensor placements affect the accuracy in step counting and stair climbing. They used five credit card size commercial accelerometer devices (activPAL™ [3]) on different positions on the leg i.e. frontal and lateral sides of upper thigh, frontal side of middle shank and frontal and lateral sides of the lower shank. They compared the observed number of steps with each sensor and recommended that mounting a sensor on the frontal side of the shank would be the best place to count steps.

Boerema et al. [11] examined the optimal place to mount a waist sensor by using five ProMove2 [4]) sensors on an elastic belt and letting the participants walk on a treadmill at different speeds. They calculated the integral of the modulus of the accelerometer output and compared the differences among sensor placements. Their conclusion was that mounting the sensor at the most lateral part of the waist is the most effective place and better results can be observed when the sensor were tightly fitted onto the belt [11].

Some of the recent analyses based on selecting the optimal sensor placements are shown in Table 2.2. Based on these results, it was realized that the 'thigh' is a better place to mount a sensor in classifying postures and some physical activities [7]. As this research focused on cyclic movements like walking, climbing stair up and down, sensors were placed on both ankles/ lower-shanks as well [10]. As most of the posture classifiers were based on waist/ chest data, two sensors were mounted

[3] https://www.palt.com/
[4] https://inertia-technology.com/product/motion-capture-promove-mini/

on the most lateral part of the waist on both sides [6, 9, 11]. According to the sensor placements suggested by Gemperle et al. [5], in this research two sensors were mounted near the rear collar area and another two were mounted on the upper arms as shown in the Figure 7.1. Finally, as the wrist is the most common place to mount a wearable device [12], two sensors were also mounted onto both wrists in this research.

2.3 Multiple Sensors in Activity Classification

Gao et al. [15] explained that there is a trade off between using a single wearable sensor data to extract a considerable amount of data on heuristic features that train complex classifiers and using multiple sensors with light-weight algorithms. In order to use multiple sensors (Shimmer sensors[1]) for their study, they attached Shimmer sensors on chest (sternum) and left under-arm on to a garment, waist sensor on a belt while a thigh sensor was placed in the pocket of the trousers. They compared the classification accuracy with a single sensor vs. multiple sensors. From a single sensor they extracted features based on time domain, frequency domain and other heuristic features and used complex algorithms with NB, ANN and decision trees. On the other hand, from multiple sensors they extracted simple features based on time domain data and used light-weight algorithms. They concluded their analysis claiming that a reasonable accuracy could be achieved with multiple sensors with basic time domain features extracted from accelerometer data.

There are publicly available datasets such as WISDM (Wireless sensor data mining) [16] and UCI HAR (University of California Irvine Human Activity Recognition) dataset [17] and those data were collected from a single accelerometer based on a smartphone. UCI HAR database consisted of data gathered from 30 participants and this database contains 561 features altogether with the row accelerometer data values. There are significant number of single sensor based research studies carried

Refrence	**Number of activities**	**Sensor Placement**	**Recommended placement**
Gjoreski et al. [9]	5 Falls detection types	waist, chest, thigh, ankle	Chest / waist
	4 Posture detection (standing, sitting, sitting on the ground, lying)		chest/waist with ankle
Montoye et al. [7]	13 activities	hip, thigh and both wrists	thigh sensor and non-dominant wrist
Cleland et al. [8]	7 activities	hip, lower back, wrist, foot, chest, thigh	hip
Lützner et al. [10]	2- step counting and stair climbing	frontal and lateral sides of the upper thigh, frontal side of the middle shank and frontal and lateral sides of the lower shank	frontal side of the shank
Boerema et al.[11]	1	Five sensors on waist line	the most lateral part of the waist
Howcroft et al. [13]	1 falls detection	accelerometers on the pelvis, shanks, head and pressure-sensing insoles	posterior pelvis which can increase the accuracy with head mounted accelerometers
Martindale [14]	12	IMUs on wrists, shoes, and in a pocket, as well as pressure insoles	all as they classified 10 cyclic activities

Table 2.2: Sensor placement in different studies and the authors' recommendation.

out based on the above mentioned databases [17, 18, 19, 20, 21, 22, 23] and based on data collected by other sensors [16, 24, 25, 26]. Some of the research studies pointed out the drawbacks of using a single sensor such as using an excessive number of features in training. Yazdansepas et al. [27] used a single triaxial accelerometer on a smartphone to classify 25 activities based on 176 features extracted from time domain features and frequency domain features. They mention that when compromising with the battery life of the phone by reducing the training dataset, they noticed that it impacted on the accuracy. Similarly, Lu et al. [28] used Arduino based sensor on a wrist to recognise six different activities based on hand movements with 160 time domain and frequency domain features. Ignatov et al. [19] used data from WISDM database and there feature vector consisted of 60 features. They claimed that in order to reduce the computation cost and time it would have been better to take smaller time windows in the analysis.

Further, Bao et al. [29] demonstrated how the activity recognition could improved by using five biaxial accelerometers while showing how the accuracy dropped when using two accelerometers. Moreover, Foerster et al. [30] also demonstrated how the multiple sensors gave support in enhancing the classification accuracy in their posture and activity classifier. There exist a significant amount of research studies carried out with multiple sensors since they improve the performance by analysing orientation of each body segment [31, 32, 33].

In this research, multiple sensors were used, as a clear picture of overall body movements could be achieved by covering both the upper body and lower body with sensors, taking into account the details mentioned in the Section 2.2.

2.4 Data Sampling in Activity Classification

Data collection from IMUs were acquired in different sampling rates taking into account the factors like saving energy and acquiring enough data [34].

Meng et al. [35] have demonstrated that common cyclical movements such as walking, running, jumping and skipping can be captured with an upper limit of 10 Hz, by analysing the power spectral of such data collected from an optical motion capture system.

Antonsson et al. [36] have analysed frequency content of gait using force plates and claimed that gait related frequencies lie between 0 and 20 Hz while 98% of the energy is below 10 Hz. Hence, Karantonis et al. [37] have used 45 Hz as their sampling rate in real time ambulatory monitoring classifier with triaxial accelerometers and Abbate et al. [38] have used 50 Hz as their sampling rate in fall detection system. Further, Abbate et al. [38] have mentioned that 50 Hz sampling rate was a good trade-off in saving energy while collecting enough accelerometer data in order to detect falls. Many other gait related studies [39, 40] and activity classifiers based on wrist data [41] have been carried out setting the data sampling rate based on Antonsson et al.'s [36] frequency analysis.

Most of the other activity classification studies (some of them have listed in Table 2.3) have used frequencies between 10 Hz and 100 Hz.

Hemmatpour et al. [42] have collected data at 10 Hz sampling rate as they have focused on falls detection and they have accomplished that identifying postural changes. Anjum and Ilyas [43] have classified simple activities such as walking, running, climbing up and down stairs, cycling, driving and inactive by collecting data at a 15 Hz sampling rate. Other studies [44, 45, 46, 48] that have collected data at 20 - 30 Hz sampling rate, have analysed common simple daily activities such as sitting, standing, walking, climbing up and down stairs, cycling and lying down. Mehrang et al. [47] also have collected data at 25 Hz. Even though they have collected data from simple activities and complex activities such as dish washing and table cleaning, they have classified all the complex household related activities as a single activity while classifying the other simple activities.

Reference	**Sensor type**	**Sensor placement**	**Activities**	**Sampling rate**
Hemmatpour et al. [42]	traxial accelerometer, triaxial gyroscope	lower back	falls detection	10 Hz
Anjum and Ilyas [43]	traxial accelerometer, triaxial gyroscope	hand, trouser pocket, shirt pocket, handbag	7 daily activities	15 Hz
Chatzaki et al. [44]	traxial accelerometer, triaxial gyroscope	trouser pocket	12 daily activities, falls detection	20 Hz
Buber et al. [45]	traxial accelerometer	front pocket of trouser	7 daily activities	20 Hz
Albert et al. [46]	traxial accelerometer	belt	falls, 4 daily activities	20 Hz
Mehrang et al. [47]	traxial accelerometer, heart monitor	wrist	4 daily activities	25 Hz
Pavey et al. [48]	traxial accelerometer	wrist	4 daily activities	30 Hz
Anguita et al. [49]	traxial accelerometer, triaxial gyroscope	waist	6 daily activities	50 Hz
Saputri et al. [50]	traxial accelerometer	front pocket of trouser	5 daily activities	50 Hz
Dernbac et al. [51]	accelerometer and gyroscope sensors of a mobile phone	User's choice	8 daily activities	80 Hz
Hsu et al. [52]	traxial accelerometer, triaxial gyroscope	wrist	10 daily activities	100 Hz
Reiss et al. [53]	Triaxial IMUs and heart rate monitor	chest, wrist, arm	18 daily activities	100 Hz

Table 2.3: Activity monitoring studies with different sampling rates [40]

Anguita et al. [49] have claimed that 50 Hz sampling rate was sufficient to capture human movements and they have classified the activities into simple activities such as standing, sitting, lying down, walking, climbing up and down stairs. Saputri et al. [50] have used 50 Hz sampling rate in classifying data into activities such as running, walking, climbing up and down stairs, hopping and jogging based on Fahim et al.'s study [54]. Fahim et al. [54] have claimed that 50 Hz sampling rate was a suitable frequency to recognise dynamic activities at an acceptable accuracy.

Dernbac et al. [51] have analysed complex activities such as cleaning (wiping the kitchen top and sink), cooking, medication, sweeping, washing hands and planting water other than the simple activities (sitting, standing,lying, walking, running, climbing stairs, and driving). That might be the reason for them to use 80 Hz as the sampling rate. Similarly, Hsu et al. [52] have used 100 Hz as the sampling rate. They have also analysed complex activities such as drinking and taking elevator other than the simple activities mentioned in Dernbac et al.'s [51] study. Reiss et al. [53] have also used 100 Hz as the sampling rate and analysed complex activities such as watching tv, computer work, folding laundry, cleaning, ironing other than the simple daily activities.

In this study, it was decided to collect data at 50 Hz sampling rate, as simple human activities can be captured and classified at an acceptable accuracy with that rate, based on the results of the other studies [49, 50, 54].

2.5 Sensor Orientation Correction Mechanisms

As sensor orientation may not be able to be maintained consistently everyday, there should be a way to correct the orientation throughout the data analysis process. That would make the data analysis procedure meaningful. In order to tackle this issue, there are two commonly followed approaches. The first approach is using the orientation invariant features and the second approach is calibrating the data based on a known/predefined position [55].

Following the first approach, some researchers conducted their analyses with the magnitude of the acceleration values so that the orientation of the sensor/device would not be affected in the classifications [56]. Hur et al. [57] also used the magnitude of the variation of acceleration without considering the orientation of the sensor. Foerster et al. [30] and Steinhoff et al. [58] also used orientation independent features in their studies by applying a calibration method to correct the position at the beginning of the data collection and using principal component analysis (PCA) to find the motion axis of the subject respectively.

Wu et al. [55] corrected the orientation by using two steps. Their first step was to detect the walking segments using magnitude of accelerometer data since magnitude did not vary with the orientation. In the second step, the training data templates (data that they collected from each participant inside the clinic) were compared with the identified walking segments to calculate the rotation matrix to fix the data. They applied this rotation matrix to the whole dataset in order to correct the orientation.

Henpraserttae et al. [59] suggested a projection-based technique to correct the orientation. First they normalised the raw data with the mean and the standard deviation of the data and next found the vertical acceleration by using the mean of the dynamic segment of the signal. Separation of the dynamic and static segments were identified by using the variance of the magnitude of the signal. Next, the anterior-posterior axis was computed using the principal axis of the data on the plane perpendicular to the vertical axis of the global coordinate system assuming that the most of the dynamic activities happen in the anterior-posterior axis. For that, first the data were projected to the plane that was perpendicular to the vertical axis and computed the principal axis of the data. The second step was performing an Eigenvalue decomposition on the covariance matrix of the data that were projected to the vertical axis to find the other two axes of the acceleration.

Friedman et al. [60] corrected the orientation based on the 'standing upright' data of the wearer. They assumed that when the sensor was attached to the body firmly and the wearer was 'standing upright', the perpendicular axis to the gravity axis should measure $0g$ (0 $gravity$). Based on this property they calculated the rotation matrix to correct the orientation.

In this research the 'standing upright' data was used to align the vertical axis of the sensor to the gravity axis and then to correct the other two axes that were perpendicular to the gravity axis by using an activity that occurs in the sagittal plane, by considering the above mentioned mechanisms regarding orientation correction.

2.6 Common Features used in HAR

In order to achieve high accuracy within a reasonable time, it is better to feed high quality features to the classifiers [61]. When creating a feature vector with a high dimension, there can be redundant data and this may cause performance deterioration in the classifiers [62]. In most of the activity classifiers, statistical heuristic features are used as the feature vectors. Statistical features that can be derived from IMU data are mean, median, standard deviation, variance, root mean square, average derivatives, skewness, kurtosis, interquartile range, zero crossing rate, mean crossing rate, pairwise correlation, spectral entropy, minimum and maximum for accelerometer and gyroscope data for each axis or magnitude for the selected time window [17].

Zhang et al. [61] introduced a feature set called physical features that are relevant to the physical movements of the activities in addition to the statistical features and they are listed below.

- Movement intensity based on the magnitude of the acceleration
- Normalised signal magnitude area

- Eigenvalues of dominant directions based on the covariance matrix of the acceleration along each axis of acceleration
- Correlation between acceleration along gravity heading directions
- Average velocity along heading direction
- Average velocity along gravity direction
- Average rotation angles related to gravity direction
- Dominant frequency based on the Fast Fourier Transform (FFT)
- Energy based on the FFT
- Average acceleration energy
- Average rotation energy

Even though some of the studies used both time and frequency based features in their activity classifiers, Chong et al. [63] claimed that subsets from time-domain features are sufficient to classify the accelerometry into activities even without analysing frequency domain features. They examined 206 time and frequency-based features with different types of classifiers (Artificial Neural Networks (ANN)), Support Vector Machines (SVM) and Random Forests (RF)) in activity classification with a single accelerometer mounted on the right hip [63].

As Chong et al. [63] suggested, only time based features were used in feature vectors including both statistical and physical features as suggested by Zhang et al. [61], in training activity recognition classifiers, in this research.

2.7 Data Fusion Methods

Data fusion can be divided into three main categories such as sensor level fusion, feature fusion and classifier fusion [64].

Banos et al. [65] and Nweke et al. [64] explained how the sensor fusion could increase the reliability, robustness and generalisation ability of a classifier. Sensor level fusion means combining raw data from multiple sources (from the same or different types) [64, 66]. For example, Chen et al. [67] and Qi et al. [68] discussed about fusion of video and IMU sensor data in human activity recognition in increasing the accuracy, while Wang et al. [69] explored fusing wearable sensor data with ambient sensor data. Most of the other studies carried out with the data collected from IMUs that are consisted of accelerometers, gyroscopes and magnetometers [66, 70, 71, 72]. Wang et al. [73] used Kalman filter [74], the most common method in data fusion to fuse accelerometer and gyroscope data. Nweke et al. [64] compared the importance of fusing accelerometer data with gyroscope and magnetometer data as these data could be used not only in removing noise but also in correcting the orientation. Nweke et al. [64] further discussed about fusing IMU data with physiological signals, pressure insole, infrared, camera, GPS, and acoustic sensor data in human activity recognition.

Orientation estimation can be done using multisensor fusion which may not an easy task in practical situations [75]. Gyroscope data can be used to estimate the orientation from a known position by using the integration [76]. However, gyroscopic data with additional noise lead to drifting problems as these errors get multiplied with the integration. Accelerometer data can be fused with the gyroscope data to correct pitch and roll estimations. Further, magnetometer data can be used in correcting yaw movements [75].

Sensor fusion works well with stationary and magnetically clean situations [75] and in order to overcome the practical issues such as linear translation of accelerometer data and magnetic interference, MARG sensor fusion algorithms combine all these sensor data.

Most commonly used MARG sensor fusion approaches are complementary filter [5],

[5] https://ahrs.readthedocs.io/en/latest/filters/complementary.html

Kalman filter[6] and gradient descent (Madgwick) filter [7].

Complementary filter uses weighted sums from accelerometer and gyroscope data. The weights are based on the reliability of the measurements depending on the frequency. This is an efficient filter with respect to computational intensity. However, with the noise, the accuracy may get inhibited.

Kalman filter uses a recursive function taking into account the current input, previous input and the previous state prediction when the situation is a linear problem and if it is not a linear problem (object with movements) extended Kalman filter can be used to linearise the parameters. This approach works well when it is tuned properly, but with a high computational intensity.

Madgwick algorithm calculates the difference between predicted and observed sensor output and minimises the difference with two gradient decent calculations. However, it was noted that the accuracy of the Madgwick algorithm hinders due to the magnetic disturbances [75]. Further, when having two gradient descent calculations, those gradients may not be perpendicular in the n-dimensional space and may affect the convergence time. The algorithm uses the horizontal component of the magnetic field to identify the magnetic north and the vertical component causes a deviation (magnetic inclination) from 0 to $\pi/2$ at the magnetic equator and magnetic poles. This may also affect the gravity vector and it may also vary from 0 to $\pi/2$. Hence, when these vectors are not perpendicular, the calculations based on yaw movements may slow down while roll direction calculations may happen faster than that.

Madgwick algorithm was modified by Wilson et al. [75], addressing the previous issues by decoupling roll and pitch from magnetic interference. Throughout this study it was decided to use this latest version of Madgwick algorithm [8].

Feature fusion means combining multiple sensor data extracted especially from het-

[6]https://ahrs.readthedocs.io/en/latest/filters/ekf.html
[7]https://ahrs.readthedocs.io/en/latest/filters/madgwick.html
[8]https://github.com/xioTechnologies/NGIMU-Software-Public

erogeneous sensors, using machine learning algorithms [64, 66, 73]. Most of the studies used handcrafted features based on time domain and frequency domain [64, 66] such as statistical features extracted from time domain signals, signal magnitude area, correlation coefficient, skewness, kurtosis and energy level of time windows [77, 78] while some studies were based on features extracted from video frames [79, 80, 81].

Classifier fusion means combining several classifiers to enhance the accuracy of the classifiers [64, 66]. There are methods that can be used to fuse data at the decision level such as bagging, soft margin multiple kernal learning, stacking, voting and hierarchical methods [82].

Even though most of the studies used data fusion in their studies, Webber et al. [66] found at their investigation that there was no evidence about the optimal level to apply sensor fusion. They noted that the computational complexity vary in different fusion levels. They observed several points through their study e.g. an improvements can be seen with accuracy and processing time when using the Kalman filter at the sensor level fusion, Bagging and stacking classifier level fusion methods are the best way to optimize fusion at classifier level fusion despite the processing time.

Throughout this research, as mentioned in the following list, it was decided to fuse the data from the sensors mounted on different places, and heterogeneous data from IMU sensors, feature fusion as well as classifier fusion following a hierarchical method.

- Sensor fusion/ sensor level
  - Using video recorded data to synchronise the IMU sensor data
  - Combining accelerometer data, gyroscope data and magnetometer data to estimate orientation
- Feature fusion / feature level

- Homogeneous sensor fusion
  - Waist sensor to vertical axis angle
  - Thigh sensor to vertical axis angle
  - Lower-shank/ankle to vertical axis angle
- Heterogeneous sensor fusion
  - Combining accelerometer data, gyroscope data and magnetometer data in orientation calculation

- Classifier fusion / Decision level
  - Static vs dynamic movement classifier - hierarchical method
  - Posture classifier (for static data)
  - Activity classifier (for dynamic data)

2.8 Clothing-Mounted Wearable Sensors in Activity Monitoring

As mentioned in Chapter 1, the bio-mechanical sensors can be either placed on/near the body or can be used as a transcutaneous sensor. The sensors that can be placed on/near the body segments can be attached with a strap, belt, or kept in shoes or attached into clothing [83]. Attachment of sensors into clothing can be done in two ways i.e. using smart textiles with electronic interconnections with sensors [84, 85, 86, 87, 88] and attaching sensors into ordinary clothing [15, 89]. However, there are some smart textile sensing approaches done with loose clothing [90].

Fabric that can sense and react to its environmental changes are defined as ‘smart textiles’ [91]. They can be divided into three types as passive, active and ultra smart textiles. Passive smart textiles are said to be the fabric that can change their features based on its environmental stimulation such as colour changing, waterproof and breathable textile. Active smart textiles can be defined as the fabric with sensors and actuators that can react to the environmental changes while passing the messages. Ultra smart textile go ahead with an additional step and can respond to the environmental changes as it consists of a brain node in addition to the sensors and actuators [92].

To embed sensors into the fabric, there are different techniques such as knitting, weaving, embroidery, coating methods and printing methods [93]. Each method has its advantages and disadvantages. Major disadvantages include having complex manufacturing processes, high production cost, limited choices in selecting fabric material and methods such as printing works better on flat surfaces [93].

However, this research focuses on long-term healthcare monitoring and only speaks about sensors mounted into ordinary clothing assuming that clothing that people wear everyday is comfortable and easy to maintain rather than using smart textile made with conductive fiber yarn [94] or conductive paint [95].

Gleadhil et al. [89] mentioned that usually tight fitting garments are being used to attach sensors, as casual clothing are loose fitting that might cause having additional movement details in the sensor readings. Further, Gleadhil et al. [89] noticed that there is little or no research to validate the measurements of IMU which are attached to the clothing (in 2018). They validated the temporal motion from the sensors attached to the clothes. They used a tight fitting vest and a tight jacket and five inertial sensor devices (weighing 23 g, with dimensions 55 mm $\times$ 30 mm $\times$ 13 mm) in their study. Two of the sensors were strapped onto the Cervical vertebra segment(C7)[9] and Thoracic vertebrae segment (T12) [10], one was placed on a jacket at C7, and the other two sensors were sewn into two pockets of a tight fitting elastic heart rate monitor vest. They focused only on dead-lifting. Using the anterior-posterior acceleration, they compared the raw error, Cohen scale, correlation and

[9] Seventh Cervical Vertebra
[10] Twelfth thoracic vertebra

mean difference of the data sets. They noticed a high similarity between the sensor values with the clothing mounted data for dead-lifting.

Most of the studies used tight fitting garments to mount sensors to collect data from multiple sensors. Gao et al. [15] used a tight fitting vest and a belt in their data collection to attach shimmer sensors to compare the activity classification accuracy with a single sensor vs multiple sensors. Most of other research studies mounted sensors onto the belts or vests of the wearer in activity classification [96, 97], Attention deficit hyperactivity disorder (ADHD) identification [98] and falls detection [99].

Further, Thu et al. [100] mounted stretch sensors on the wearer's garment near the knee and Tsirtsi et al. [101] mounted IMUs onto a vest to implement activity classifiers. On the other hand MCGrath et al. [102] used a sports vest to mount an IMU to detect fast bowling in cricket and Smith et al. mounted an IMU on a sports vest to detect locomotion of athletes [103].

However, tight fitting clothing are not comfortable to be worn for an extended period of time [90]. It is also uncomfortable, especially for elderly people and people with movement disorders. Even though, the usage of loose clothing can address this issue, there would be a trade off with the sensor reading accuracy as the sensors might get disoriented and can add additional movement data to the sensor reading [90].

In 2002, Laerhoven et al. [104] described how they achieved a higher activity recognition rate when using 30 accelerometers. They formed a harness with 16 sensors and mounted them on the legs. The rest of the sensors were mounted covering the upper body and those sensors were attached onto loose clothing using velcro.

Michael et al. [105] conducted their study as a simulation of collecting data from loose clothing. Instead of collecting data from people, they collected data from a pendulum with tri-axial accelerometers mounted into three different fabric materials (denim, jersey and roma). The fabric was attached to the end of the pendulum.

Three accelerometers were attached in such a way that one was at the tip of the pendulum, the second one was at the middle of the fabric and the last one at the end of the fabric. After attaching the calibrated sensors, the pendulum was released from the horizontal position and data collected for 10 seconds. The experiment was done with and without using an additional weight at the end of the pendulum to check whether there was an affect to the data with that additional weight. Michael et al. revealed that the sensors mounted onto the clothes instead of strapping them with non-rigid bands might give a better signal variation that would make the activity recognition procedure easier [105].

Chiuchisan et al. [106] mounted an Arduino Nano board with an IMU into a loose pair of trousers on the thigh area. They called it the 'wearable recovery pants' as they intended to use them for the elderly or people with disabilities in their rehabilitation time periods to detect movements. They analysed the data collected from the sensors and concluded that there is potential for using such loose clothing with sensors in clinical rehabilitation.

Jia et al. [107] used a device called eButton which can be mounted onto the wearer's top so that the device could touch the wearer's chest. They have successfully used the IMU readings of the eButton which can be mounted onto everyday wear clothing to observe ballistocardiogram (BCG) signals.

Yudantoro et al. [108] mounted 10 IMUs on to a shirt to detect falls in real time and they focused mainly on the passing of messages in real time when they detect a fall.

To date, there are a few studies that were carried out analysing how the loose clothing mounted sensor data vary from body mounted sensor data. One such study was based on the upper body mounted sensor data in a loose garment [90]. Harms et al. [90] performed this study under a shoulder rehabilitation programme and they calculated the orientation error between a simulator output and the clothing, for 10 different postures. Then they enhanced their simulator with the calculated orientation errors and validated their simulation. They concluded that they noticed an increment in posture classification accuracy by 18% when they corrected the simulation.

It was identified that there should be a systematic way of analysing how clothing-mounted sensor readings would differ from body-mounted sensor data. Further, it was noted that, almost all the other studies based on loose clothing, mounted the sensors on top of the clothing other than the study conducted by Chiuchisan et al. [106]. Their research investigated how the sensors mounted inside the lateral part of the everyday wear clothing, support in activity classification [106].

2.9 Discussion and Conclusion

This research uses multiple IMU sensors consisting of accelerometer, gyroscope and magnetometer in order to analyse the movement patterns of people. In order to make the donning and doffing of sensors easier, the sensors would be mounted onto clothing. The optimal places to have the sensors to track the movements of people have been discussed under Section 2.2, and accordingly this research covers both the upper body and lower body with sensors.

During the data collection, sensors might not be able to keep the same orientation across all days and the sensor placement might change after the participant wore the clothing. Hence, a sensor orientation correction mechanism was used in this research.

According to the literature, this research uses time based statistical and physical features to train the activity classifiers. Data, features and classifier outputs fuse where necessary as described in Section 2.7 to enhance the output of the classifiers.

Even though some studies used loose clothing in their data collections, there seem to be a gap in the validation of loose clothing data with respect to different activities. Hence, this research focuses on quantifying the use of loose clothing data and understanding human movements based on clothing data with respect to basic postures and gait parameters.

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Chapter 3

Comparing Clothing-Mounted Sensors with Wearable Sensors for Movement Analysis and Activity Classification

This chapter addresses the first aim of this research and it was to quantify how strongly sensors mounted onto body correlate with sensors on clothing depending on different activities and clothing types.

In order to achieve this aim, a single person study was conducted with 4-6 Actigraphy sensors[1] across three days. The sensors were mounted as pairs near waist, thigh and ankle depending on clothing type (loose slacks, pencil skirt and knee length dress). The participant performed multiple daily activities such as walking, running, sitting and riding a bus. The main analysis was based on comparing the Similarities between accelerometer signal pairs (on body and clothing) by calculating correlation coefficients for different activities and clothing type.

[1]http://www.actigraphy.com/

By conducting this analysis, three main conclusions were able to derive. Higher correlation values were observed while the person was in static postures and slightly lower correlations were observed while the person was performing dynamic activities such as running and walking. Further, the activity classification accuracy of clothing mounted data were compared with body-mounted data as the ground truth and noted that the clothing dataset also has g a reasonable accuracy in activity classification.

Methodology, discussion and conclusions are explained in detail on the attached paper titled "Comparing Clothing-mounted Sensors with Wearable Sensors for Movement Analysis and Activity Classification".

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Comparing Clothing-Mounted Sensors with Wearable Sensors for Movement Analysis and Activity Classification

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Abstract: Inertial sensors are a useful instrument for long term monitoring in healthcare. In many cases, inertial sensor devices can be worn as an accessory or integrated into smart textiles. In some situations, it may be beneficial to have data from multiple inertial sensors, rather than relying on a single worn sensor, since this may increase the accuracy of the analysis and better tolerate sensor errors. Integrating multiple sensors into clothing improves the feasibility and practicality of wearing multiple devices every day, in approximately the same location, with less likelihood of incorrect sensor orientation. To facilitate this, the current work investigates the consequences of attaching lightweight sensors to loose clothes. The intention of this paper is to discuss how data from these clothing sensors compare with similarly placed body worn sensors, with additional consideration of the resulting effects on activity recognition. This study compares the similarity between the two signals (body worn and clothing), collected from three different clothing types (slacks, pencil skirt and loose frock), across multiple daily activities (walking, running, sitting, and riding a bus) by calculating correlation coefficients for each sensor pair. Even though the two data streams are clearly different from each other, the results indicate that there is good potential of achieving high classification accuracy when using inertial sensors in clothing.

Keywords: actigraph; body worn sensors; clothing sensors; cross correlation analysis; healthcare movement sensing; wearable devices

1. Introduction

In many countries, a significant increase can be seen in the number and proportion of older adults year on year. The population of people over 60 years old is projected to increase in Europe, Northern and Latin America, Asia and Africa from the year 2015 to 2030 [1]. The number of people who have noncommunicable diseases is also projected to increase significantly by 2030 [2]. Generally older people are more prone to noncommunicable diseases [2] resulting in high care costs in each country. In OECD (Organisation for Economic Co-operation and Development) countries, an annual increment of 4.8% of the cost allocated for long-term monitoring from 2005 to 2011 was seen. It is predicted that this cost will double in the period from 2015 to 2060 [3].

Home-based monitoring potentially offers a cost-effective mechanism for prevention of disease and promotion of healthier lifestyles. A number of factors have to be taken into account when using a long-term monitoring system, such as whether these systems are reliable for measuring real time data, are safe to use with patients, have high power efficiency, and provide clinically useful data. Wearable sensors have the capability to provide efficient monitoring of daily routines for a long period in a cost effective way [4].

A growing interest in health monitoring has led to the commercial availability of a number of wearable sensors for self-monitoring. Consumer products for self-monitoring generally comprise a single device, often wrist worn, which may hinder the accuracy of the data analysis and classification. In contrast, in research work, multiple sensor devices are often used in order to achieve a higher accuracy in activity classification. However, there are feasibility issues with the wearing of multiple sensors on a daily basis in a residential environment. There are also challenges in maintaining a consistent sensor orientation and approximate location with respect to the body during the data collection periods. Further, in healthcare the patient or research participant may not have the patience, or abilities to attach multiple sensors each day. Embedding sensors into the clothing may, to some extent, address both issues of wearing multiple sensors every day and managing the sensor orientation and approximate location.

This study considers the quality of data that would arise from inertial sensors embedded into clothes that people wear on a daily basis.

It examines whether these sensor devices would be able to provide data as accurate as that collected by sensors attached to the person. In particular, can the data be used to predict the actions and behaviour of the individual and allow activity classification?

The aim of this research is to investigate and quantify to what extent the data obtained from the clothing sensors can be used in characterising activities, as compared with body worn sensor data. To achieve this, sensor data were collected from body worn sensors and sensors attached to three different clothing types, across a range of daily activities. The correlation coefficients were calculated between the clothing-embedded and worn data to check how much they agree with each other across a range of daily activities and different styles of clothes.

2. Related Work

Research relating to the use of wearable sensors with older adults has largely been in three areas – indoor tracking, activity classification and real-time vital sign monitoring [5]. Activity classification using body worn inertial sensor data in long-term monitoring is a well-established approach [6]. Accelerometers are being used as the key instrument, while gyroscopes and barometric pressure sensors are also used in some studies. Out of those studies some are using a single sensor while others are using multiple sensors for activity recognition. For example, a single sensor, i.e., a sensor only on the waist, thigh, lower-back and thigh, in activity classification of the whole body can be seen respectively in [7–10]. Other studies, using multiple sensors, investigate the accuracy of activity classification compared across placement of the sensors on the wrist, hip, neck, knee, chest, lower arm, lower back, upper arm and ankle. Montoye et al. [11] observed high accuracy in activity classification for three levels of physical activities, i.e., SB (sedentary behaviour), LPA (light-intensity physical activity) and MVPA (moderate-to vigorous-intensity physical activity) based on thigh data, high accuracy in classifying SB based on (non-dominant) wrist data, and low accuracy in classifying physical activities based on (dominant) wrist and hip data. Hence, they concluded that it is better to use thigh data or non-dominant wrist data in analysing different levels of physical activities. Cleland et al. [12] found that, of chest, wrist, lower back, hip, thigh and foot sensor data, hip data scored the highest accuracy in activity classification. However, they [12] also noted that further studies should be carried out in order to find the optimal sensor placement across multiple activities, since their study focused only on activities such as walking, lying and sitting. As both upper body and lower body movements contribute to locomotion [13], it is better to investigate movements from both sides of the body, rather than just one side.

Analysis of above mentioned sensor data related to activities may seek to find patterns of activities or movement quality. In most of the studies, pattern recognition algorithms were used in activity classification, such as decision trees ([10,14,15]), KNN (k-nearest neighbours algorithm) ([15–17]), SVM (Support Vector Machine) ([9,18,19]) and other algorithms (C4.5, RF (Random Forest), NB (Naive Bayes), Bayesian).

Even though there are numerous research studies on activity classification with sensor data, very few have been conducted on sensors attached to everyday clothes. One study highlighted that there was little to no research validating the measurements of IMUs (Inertial Measurement Unit) attached to loose clothes [20]. Their research aimed to validate the temporal motion from the sensors attached to the clothes. As the clothes, a tight fitting vest and a tight jacket were used. Their main intention was to validate the sensor readings by calculating four parameters, i.e., raw error, standardised error (Cohen scale), Pearson's correlation and mean difference. Five inertial sensor devices (weighing 23 g, with dimensions 55 mm $\times$ 30 mm $\times$ 13 mm) were used, where two were strapped onto the Cervical vertebrae segment(C7) and Thoracic vertebrae segment (T12), one was placed on a jacket at C7, and the other two sensors were sewn into two pockets of a tight fitting elastic heart rate monitor vest so that they were posterior to the C7 and T12 sensors. The study focused on only one activity, that is, dead-lifting. When comparing the raw error, Cohen scale, correlation and mean difference of the data sets, only the anterior-posterior acceleration was used. They were able to see a high similarity between the sensor values that were obtained from both mechanisms, owing to the single activity that they conducted with the tight clothes.

A second research study reported that sensors mounted onto clothes, instead of strapping them onto a structure with rigid bands, gives a better signal variation so that it may make the activity recognition procedure easier [21]. For their data collection, a pendulum and three different fabric materials (denim, jersey and roma) and three tri-axial accelerometers were used. The fabric was attached to the end of the pendulum and three accelerometers attached such that one was at the tip of the pendulum (fixed in place with a rigid band), a second one was in the middle of the fabric, and a third was at the edge of the fabric. After attaching the calibrated sensors, the pendulum was released from a horizontal position and data was collected for 10 seconds. The experiment was done with and without an additional weight at the end of the pendulum. The Euclidean distance and one-way analysis of variance were calculated when calculating the similarity of the signals (data from sensors attached with rigid bands as compared with sensors attached to different fabric materials). The objective was to predict whether the pendulum was swinging with or without a weight attached to the end. For this prediction, SVM and DRM (Discriminative Regression Machines) were used. The conclusion of their research work was that the fabric's nature of deforming movements in various directions makes it easier to predict the motion, compared with the sensor data obtained from the sensors attached with the rigid bands.

Hence it can be concluded that more information is needed to assess the true value of embedding sensors into clothing to allow better representation of human movement and activity classification.

3. Materials and Methodology

The aim of the present study is to compare and contrast how clothing sensor data patterns correlate/deviate from body worn sensor data, across three different types of clothing.

3.1. Data Collection Procedure

Data were collected from one participant (the first author) over three normal working days. On each day, the participant wore a different type of clothing (loose slacks, pencil skirt, and frock/knee-length dress), and multiple sensors were worn in pairs on the clothing and the body. The sensors and their placement are described further in the next section. An activity log was kept and used to annotate the data files. The main activities were walking, running, sitting as well as other daily activities including riding on a bus.

3.2. Sensor Placement

Actigraph tri-axial accelerometers (wGT3X-BT, weighing 19 g and measuring 4.6 cm $\times$ 3.3 cm $\times$ 1.5 cm, as shown in Figure 1) were worn in pairs, such that one sensor was strapped onto the body and the other was sewn to the clothes in a similar location to the body-worn sensor. As the optimal places to mount sensors are not yet well defined [12], we mounted one sensor pair on the waist to track upper body movements, and two other sensor pairs on the upper thigh and ankle to track lower body movements [13]. Hence, sensor pairs were placed at the participant's waist and upper-thigh for the pencil skirt (41 cm long, with a 38 cm inch perimeter at the thigh) and the frock (48 cm inch perimeter at the thigh). For loose slacks, a further pair of sensors was worn on the ankle and hem of the slacks. The body worn sensors were always placed just below the sensors on the clothes, as shown in Figure 2. The participant was 152 cm in height, and wore UK women's size 6 clothes. The orientation of the sensors was set such that the y-axis was aligned most closely to the axis of acceleration from gravity. Table 1 shows the duration of data collection, type of clothing and sensor placement.

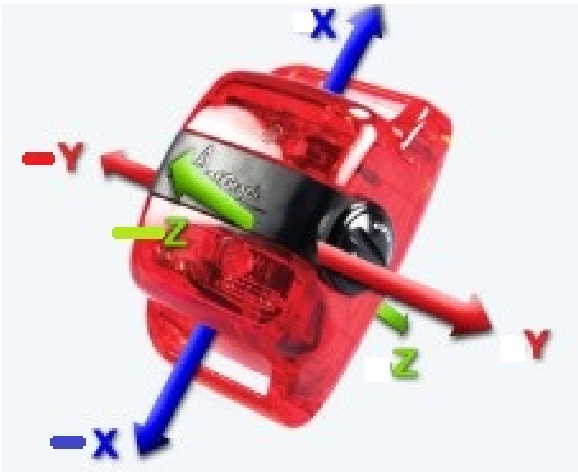

Figure 1. Coordinate frame of the Actigraph device. (Image from Actigraph website https://www.actigraphcorp.com).

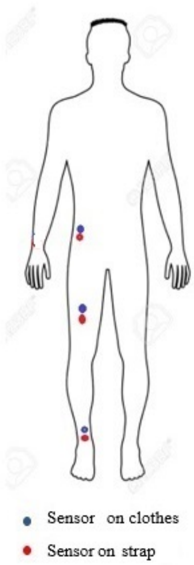

Figure 2. Sensor placement on subject and on subject's clothes.

The sensor devices were initialised with the Actilife (https://www.actigraphcorp.com/support/software/actilife/) software to synchronise their internal clocks. Additionally, at the start of each day of data collection, the participant performed a jump in order to create a distinctive marker in the accelerometry data that could be used to further check the synchronisation. Furthermore, each pair of sensors (one in clothes and one on the body) were tapped synchronously four times to ensure data from sensor pairs could be time-aligned. At the end of each data collection period, another jump was performed to identify the point where the data collection was completed, and provide an indication of any potential sensor time drift.

Table 1. Sensor placement over three days and three types of clothing.

		Day 1	Day 2	Day 3
Clothes		Loose slacks	Pencil skirt	Frock (knee-length dress)
Duration		5 hours	3 hours	3 hours
Frequency		50 Hz	50 Hz	50 Hz
Sensor placement	**on Body**	Waist	Waist	Waist
		Right thigh	Right thigh	Right thigh
		Right ankle	n/a	n/a
	on Clothes	Waist band of slacks	Waist band of skirt	Waist band of frock
		On seam of slacks near thigh	On seam of skirt near thigh	On seam of frock near thigh
		Hem of slacks near ankle	n/a	n/a

3.3. Data Analysis

The data were analysed in terms of sensor pairs, in order to compare the body worn with the clothing worn data. Comparisons were also made across different activities and the different clothing types. The data were analysed in MATLAB.

3.3.1. Preprocessing the Data

The data from both sensors in a pair were first time-aligned, based on the "jump" and the "tap" markers. Next, the time lag between the two sets of sensor readings for each activity was estimated using a cross correlation, because there can be time lags between the body-worn and the clothing-mounted sensor readings owing to factors such as the stiffness of clothing material (which causes swing) and cloth dynamics for each activity. The maximum cross correlation value was then used to determine the lag between the two signals, and this lag was adjusted in order to bring the two signals into alignment.

Secondly, an orientation correction was applied to both sets of data. When attaching the sensors onto the body and to the clothes, there may be discrepancies in the orientations between the two sensors in a pair. Hence in order to maintain a reasonably similar orientation for each sensor pair, each data set was rotated along a common axis so as to align the principal direction of gravity with the y-axis of the sensor. This correction can be computed easily using Rodrigues' rotation formula [22] and identifying the axis of rotation as being perpendicular to both the gravity vector and the y-axis, and the rotation about this axis is therefore the angle between these two vectors. Data where this rotational correction has been applied is termed the 'rotated data set'.

These preprocessing techniques were carried out in order that the data from the two sensors in each pair could be meaningfully compared.

3.3.2. Activity Extraction

Using the activity log, data segments corresponding to four activities (walking, running, sitting, bus ride) were extracted for each day/clothing type. From these segments, three shorter instances (30–40 s/1500–2000 data points) of each activity were identified and extracted for further analysis.

3.3.3. Comparing the Similarity of the Body-Worn and Clothing-Mounted Sensors

After establishing the normality of the data [23], Pearson's correlation coefficient was calculated for each sensor pair to assess the strength of the linear relationship between the two signals [24].

3.3.4. Activity Classification

We also wished to investigate the possibility of using the clothing sensor data in activity classification as productively as the body worn sensors. For this purpose, the data were categorised into four classes: walking/running, transition of a movement, sitting and standing. The analysis examined only the 'thigh' sensor data. When a subject is sitting, the thigh is often in a perpendicular posture with respect to the standing posture, hence sitting and standing would be more easily distinguished with thigh sensor orientation data as compared with waist or ankle sensor data.

Furthermore, the y-axis accelerations (gravity axis) were used for the classification, because this axis exhibited the most noticeable differences across activities in acceleration values. When a subject is standing, the gravity axis acceleration is (following alignment) close to the y-axis value. When the subject is sitting, the y-axis is now perpendicular to the gravity vector so values are close to zero. When the subject is moving, the y-axis values are changing significantly based on the additional accelerations that result from these movements.

The features used for classification were chosen to emphasise information about posture and movement, including movement transitions. Transitions include sit-to-stand/stand-to-sit activities which would cause the y-axis acceleration to increase/decrease suddenly, sit-to-walk/run could again increase the acceleration suddenly, and walk/run-to-stand would cause a sudden reduction of the acceleration. Two features were used in this classification. To track postural changes, the y-axis acceleration values were used, while the moving variance of the y-axis acceleration values was calculated to track these transitions. A window size of 250 milliseconds was chosen to ensure that even the acceleration changes in short periods were captured.

A decision tree was implemented to classify the data into activities by defining threshold values, based on visual inspection, for the y-axis (gravity) acceleration and the y-axis moving variance values. Threshold values were estimated for both body-worn and clothing-mounted sensor data.

Both body worn and clothing data files were then classified into activities by using the decision tree. Finally, a confusion matrix was created to observe how the classification outputs differed from body worn data and clothing sensor data, by considering the classifications of body worn sensor data as the benchmark data set.

4. Results

4.1. Activity-Wise Time-Alignment

Figure 3 illustrates the cross correlation values plotted over time for one of the running data segments. The point at which the cross correlation reaches a maximum value indicates the lag between the two signals. The graph shows Day 3 (Frock) running data from the thigh sensor, and for this specific activity, the lag was 38 data points (approximately 0.76 s delay).

After adjusting for the delay based on the cross correlation maximum value, the time-aligned signals are as shown in the right-hand plots in Figure 3, with a maximum cross-correlation now appearing at 0 s, indicating that the delay between the two signals was minimised after applying this technique. When the correlation coefficient is calculated without considering this time lag, for this running instance, the value was 0.4136 and after the lag was corrected the correlation coefficient value was 0.6345. Likewise, the time lag between body worn and clothing worn data set for each activity segment was calculated and corrected before examining the correlation coefficient values for each activity.

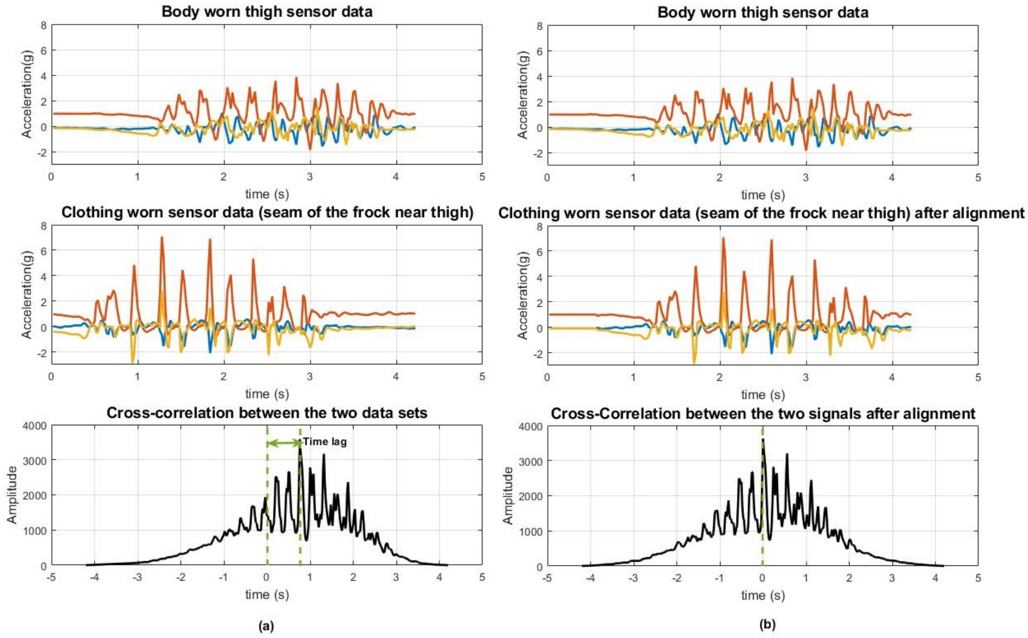

Figure 3. (**a**): Left side 3 plots: Tracked time lag between body worn and clothing sensor data for running when the subject was wearing a frock, (**b**) Right side 3 plots: Signals after the alignment using cross-correlation value. (**b**) After alignment, maximum cross correlation was observed at 0 s.

4.2. Descriptive Analysis of Acceleration Data

Figure 4 illustrates walking data extracted from thigh and ankle sensor pairs when the subject was wearing slacks. The sensors were on the right leg, thus two peaks can be interpreted as a single stride (2 steps) as indicated. According to the data it was calculated that typical stride (two steps) time here was approximately 0.7 s.

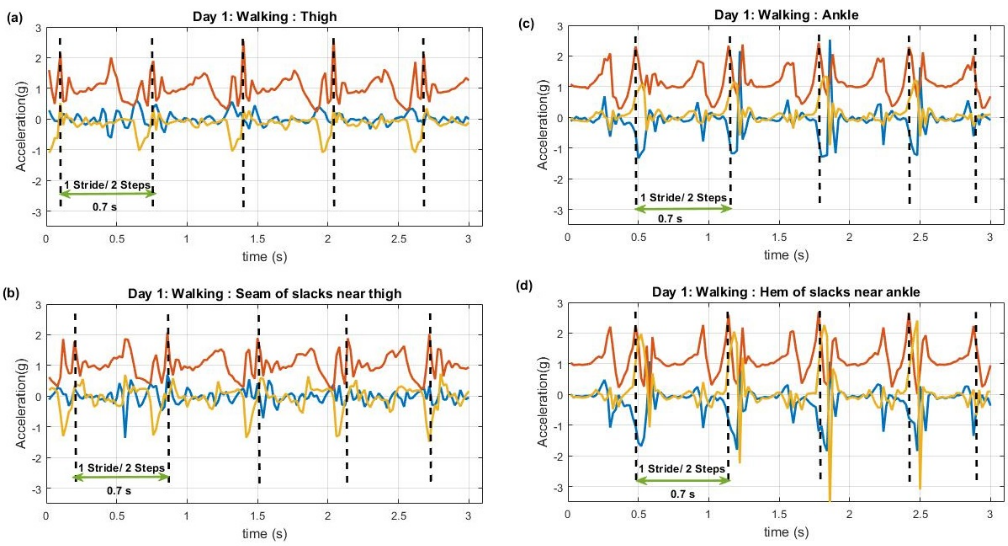

Figure 4. Walking from Day 1 (slacks). (**a**): Data from thigh worn sensor, (**b**): Data from seams of slacks near thigh, (**c**): Data from ankle worn sensor, (**d**): Data from hem of slacks near ankle. Red axis: vertical acceleration, Blue axis: anterior-posterior acceleration, yellow axis: mediolateral acceleration. Note the similarity of signals between clothing and body worn sensors for walking

Figure 5 shows running data from the sensor pairs that were on (and over) the thigh when the subject was wearing a pencil skirt (left graphs) and frock (right graphs) respectively. According to these data it can be seen that typical stride time (two steps) for running was approximately 0.3 s. Even though the acceleration values of pencil skirt data have relatively similar values with body worn sensor data, the frock data in contrast comprise higher acceleration values with sharp peaks when compared to body worn data.

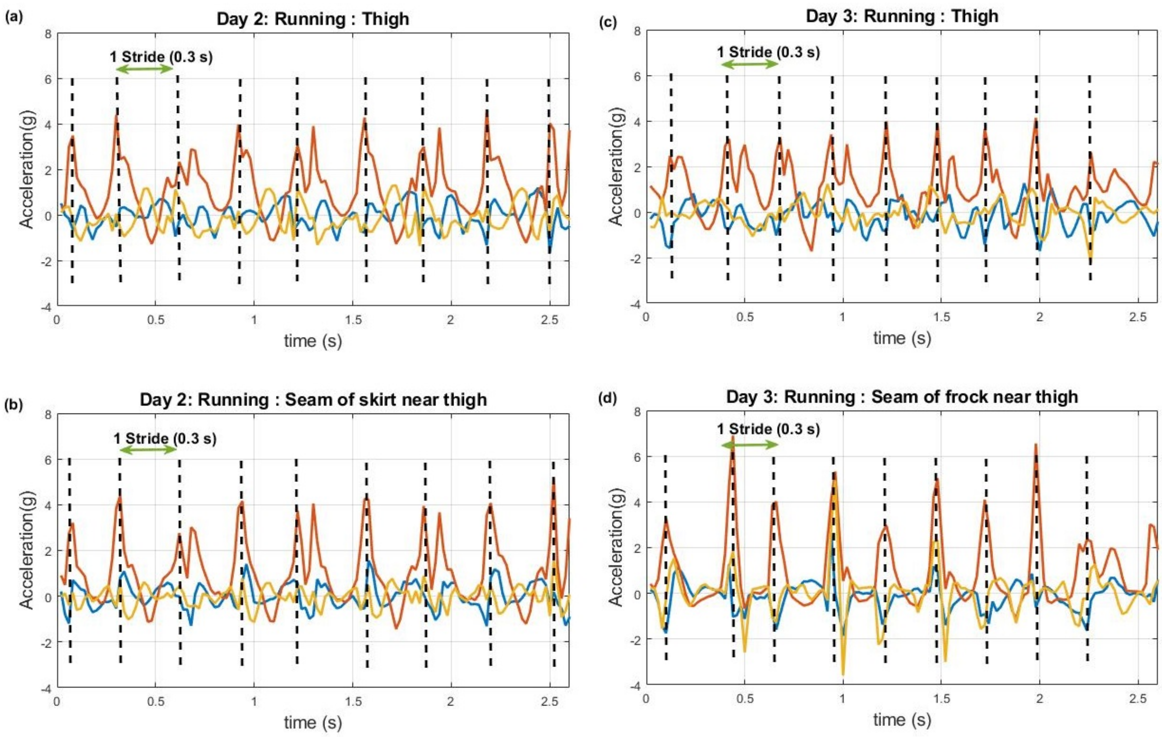

Figure 5. Running data from Day 2 (Skirt; left graphs) and Day 3 (Frock; right graphs). (**a**): Day 2 data from thigh, (**b**): Day 2 data from seams of skirt near thigh, (**c**): Day 3 data from thigh, (**d**): Day 3 data from seams of frock near thigh. Red axis: vertical acceleration, Blue axis: anterior-posterior acceleration, yellow axis: mediolateral acceleration. Note the similarity of signals between clothing and body worn sensors for skirt data verses the high accelerations present in frock data.

4.3. Correlation Coefficient Value Analysis

When examining the correlation coefficient values, five different sets of data were compared to determine from which data set the maximum correlation coefficient could be found. The five different data sets were the original data set, the time aligned data set, rotated data along the gravity axis, time-aligned and rotated data and finally the time-aligned, rotated and activity wise time-aligned data. After comparing all the values, it was noted that for activities like walking and running, maximum correlation coefficient values were found after applying a rotation matrix and activity-wise alignment.

Table 2 shows correlation coefficient values for each activity (multiple walking, running and sitting segments) after applying a rotation matrix and activity-wise alignment. They are listed by clothing type (slacks, skirt and frock) for both waist and thigh sensor data.

From Table 2, the waist sensor data had the highest correlation coefficients, irrespective of clothing type. However, thigh data also showed reasonable correlation values for each activity depending on the clothing type.

Table 2. Median correlation coefficient values for different activities for different clothes based on the 'Waist' and 'Thigh' sensors. Where there were multiple instances of the same activity in a day, the correlation coefficient was calculated for each instance, and the median and variance of the multiple instances is shown. There was a good correlation between body-worn and clothing sensors, apart from the sensor pair on the thigh and seam of the frock.

	Slacks		Skirt		Frock	
	Waist	**Thigh**	**Waist**	**Thigh**	**Waist**	**Thigh**
Walking	0.985± 0.022	0.945± 0.013	0.991± 0.006	0.973 ± 0.013	0.978 ± 0.018	0.921 ± 0.059
Running	0.811 ± 0.065	0.802 ± 0.067	0.926 ± 0.0007	0.835 ± 0.094	0.901 ± 0.008	0.642 ± 0.014
Sitting	0.993 ± 0.014	0.967 ± 0.001	0.999 ± 0.0002	0.995 ± 0.004	0.974	0.705
Bus Ride	0.988	0.987	-	-	-	-

4.4. Activity Classification

Figure 6 shows a segment of the output of the activity classifier, based on both body worn and clothing sensors (thigh data on the slacks). This classifier attempted to identify activities i.e., walking/running, transitions, sitting and standing, as denoted on Figure 6. In addition to the classification results, the activities performed by the participant as recorded in the diary are indicated on both graphs.

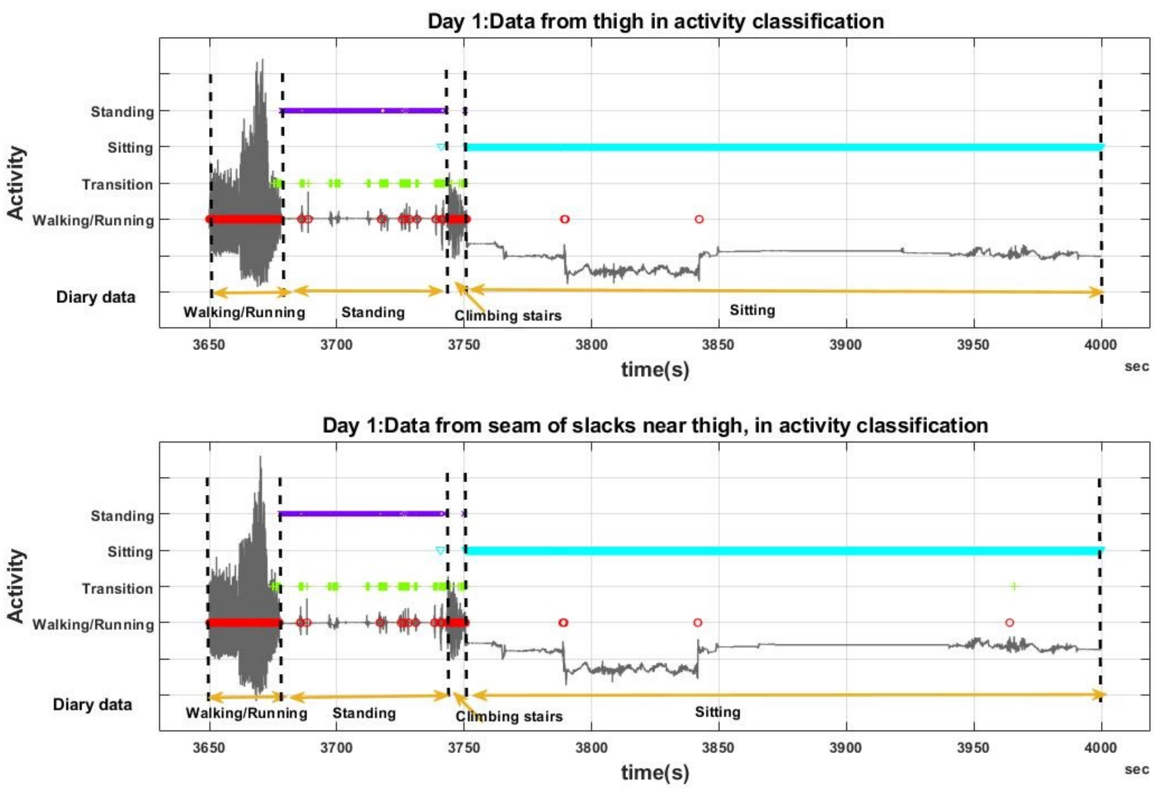

Figure 6. Activity recognition using a decision tree: Day 1 (slacks) data from body worn (top graph) and clothing sensors (bottom graph) were classified into one of four activities i.e., Walking/Running, Transitions of activities, Sitting and Standing. This figure shows a segment of the day's data. The gravity axis acceleration is plotted in grey, and the outputs of the classifier are denoted in different colours. Red: Walking/Running, Green: Transitions, Cyan: Sitting, Purple: Standing. The participant's activities according to the diary data are also shown in yellow. The outputs of the classifier are similar in both data files, with minor mismatches.

As the main intention of this research was to examine how the classifier outputs for the clothing sensor data compared with those from the body worn sensor data, and not to calculate the “true” activity classification accuracy, a confusion matrix (Table 3) was created considering the classifications from the body worn data set as the true class. For example, the first cell (row 1, column 1) of Table 3 indicates that 88.0% of the data that was classified as “walking” based on the body worn sensor are also classified as walking based on the clothing worn sensor. Similarly, 9.5% of the data classified as walking based on the body worn sensor are classified as transitions based on the clothing worn sensor.

Table 3. Confusion matrix showing the level to which activity classification based on the clothing sensor data was in agreement with classification based on the body worn sensor data (Day 1 data: when the subject was wearing slacks). Green boxes show when the highest value was expected and also achieved, Yellow boxes indicate where a high value was expected, but a lower value than expected was observed.

		Classification Data from Clothing Worn Sensor against Body Worn Data			
		Walking	**Transitions**	**Sitting**	**Standing**
Classification Data from the Body Worn Sensor as the “True” Class	**Walking**	88.00%	9.50%	0.70%	1.8%
	Transitions	16.10%	45.58%	11.42%	26.90%
	Sitting	0.32%	0.26%	88.37%	11.05%
	Standing	1.20%	9.58%	0.08%	89.14%

5. Discussion

When using correlation coefficients to compare the data sets, it was important to perform a data alignment for all the sensors, as the correlation was affected by time lags between the sensors’ starting times. Orientation correction at this level is also important as the sensors can become misplaced while the subject is moving and it can mislead the comparisons of data sets. The long term goal is to eliminate the need for time lag and orientation correction by embedding the sensors more effectively in the clothes and engineering synchronous data readings.

The first analysis was done calculating correlation coefficient values for both data files. Table 2 was prepared with a summary of all data from the four common activities that were conducted on three days for waist and thigh sensors. It was clear that thigh data were less correlated than waist sensor data sets. Yet, these values were also significantly correlated with each other. The frock data indicate the possibility of considering clothing dynamics in the sensor data as the frock was a loose dress. Thus the frock could swing with the movements of the leg when the subject was running and walking. Further, when the subject was sitting on a chair, it was noted that the sensor on the clothes near the thigh tended to shift with respect to the sensor worn on the thigh itself. Typically the sensor on the frock would fall away from the leg and onto the chair thus losing a strong relationship to the underlying limb. In addition to the swinging attribute of the frock, the weight of the sensor device (Actigraph) emphasised the movement of the clothing rather than the body. Even though there are no established measures of the looseness of clothes relative to body size, clothing sensor readings would allow these concepts to be explored.

The final analysis was the comparison of the outputs of the activity classifiers. Based on the confusion matrix (Table 3), it was noted that all the activities except the transitions were identified in a high true positive rate, i.e., more than 80%, where the classifier output based on the body-worn sensor was considered as “true”. Hence it can be taken as a positive indication that this would work more accurately when an advanced classifier would be used in activity classification. The findings of [21], mentioned that the accuracy of activity recognition was higher when the sensors were mounted onto clothes. However, they collected the data from a cloth attached to a pendulum. When it comes to data collection from a human with actual clothes, it could be said that our evidence demonstrates a more complex relationship. However, it should be noted that owing to the weight and the size of the

Actigraph devices, the correlation of data could have been decreased, and it is better to use smaller, lightweight sensors in a study like this.

When clothing worn sensor data is used for activity classification, it is reasonable to expect that the results will depend on factors that include subject characteristics (e.g., size, gender) as well as clothing styles (looseness, placement). However this study is intended to assess the viability of this approach and hence considers only a single subject across three different clothing types. In future studies, if the sensor positions may vary slightly from day to day due to different positioning of the clothes on the body, this issue can be minimised by rotating the three axis sensor readings along a common axis so as to align the principal direction of gravity with the y-axis of the sensor. Moreover, the data distribution for each activity is expected to be the same for x, y and z axis acceleration for sensor readings from different positions. Out of the three types of clothing, the pencil skirt data had the highest correlation as it was the tightest fitting of the clothing used in the study. Moreover, as the clothing waist sensors were more tightly attached to the waist with the clothes, waist sensor data were significantly correlated with each other irrespective of the clothing type.

6. Conclusions

This study aimed to assess the suitability of clothing sensor data for use in activity recognition when compared to similarly placed body worn sensors. In this study the clothing sensor data are shown to be well correlated with body worn sensor data as indicated by an analysis of correlation coefficient values. Furthermore the classification results from the clothing sensors are promising when compared to body worn sensors. This is a first study reporting data from sensors embedded into loose clothing in everyday activities. Results indicate that this approach has good potential for daily monitoring, for example in healthcare applications, and that this is an area worthy of further investigation.

This was a single person study intended to gain insight into how data might vary across three different clothing types across a range of likely daily activities. As such the study does not consider benefits of the wide range of different algorithms that could be used for classification. Rather the study checks whether it is possible to collect meaningful data from clothing worn sensors compared to body worn ones. Future studies are now encouraged to improve activity classifiers based on clothing types and supporting the use of multiple lightweight sensors that are networked and time synchronised.

All data used in the paper is available at 10.5281/zenodo.3597391.

Author Contributions: Conceptualisation, U.J., W.S.H. and F.H.; methodology, U.J.; software, U.J.; validation, U.J.; formal analysis, U.J., W.S.H. and F.H.; investigation, U.J., W.S.H. and F.H.; resources, U.J., W.S.H. and F.H.; data curation, U.J.; writing—original draft preparation, U.J.; writing—review and editing, ALL; visualization, U.J.; supervision, W.S.H. and F.H.; project administration, W.S.H.; funding acquisition, U.J., W.S.H. and F.H. All authors read and approved the final manuscript.

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Chapter 4

Loose Clothing Mounted IMU Data From Lower Body for Everyday Activities

This chapter explains the data collection protocol followed in the main data collection of this research. This covers the second aim of the research i.e. collecting a semi-natural dataset from loose clothing-mounted lightweight IMUs and making it a publicly available dataset so further research can carry out with the dataset.

5 healthy adults took part in this data collection and each participant wore the clothing with sensors for 1-4 days for 5-8 hours. The data collection is consisted of 15 participant-days worth data and it is roughly 90 hours of data. Even though the data were collected from both upper and lower body, the database is consisted of data collected only from the lower-body.

This data collection protocol was approved by the ethics committee at the School of Biological Sciences, University of Reading, UK (SBS 19- 20 31 and SBS 21- 22 18) and the approvals are attached under Appendices (Appendix A).

As these IMU data contains data from accelerometers, gyroscopes and magnetometers, there is an opportunity of creating more handcrafted features in improving classifier accuracies. Further, as the dataset includes data for activities such as 'sitting-to stand', 'turning' and 'leg raising', researchers who are interested in analysing transitional activities and postures can use these data in analysing them.

Methodology, protocol, data storing, decoding and wrangling approaches are explained in details on the attached paper titled "Inertial Measurement Data From Loose Clothing Worn on the Lower Body During Everyday Activities".

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Inertial Measurement Data From Loose Clothing Worn on the Lower Body During Everyday Activities

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ABSTRACT

Embedding sensors into clothing is promising as a way for people to wear multiple sensors easily, for applications such as long-term activity monitoring. To our knowledge, this is the first published dataset collected from sensors in loose clothing. 6 Inertial Measurement Units (IMUs) were configured as a 'sensor string' and attached to casual trousers such that there were three sensors on each leg near the waist, thigh, and ankle/lower-shank. Participants also wore an Actigraph accelerometer on their dominant wrist. The dataset consists of 15 participant-days worth of data collected from 5 healthy adults (age range: 28 - 48 years, 3 males and 2 females). Each participant wore the clothes with sensors for between 1 and 4 days for 5-8 hours per day. Each day, data were collected while participants completed a fixed circuit of activities (with a video ground truth) as well as during free day-to-day activities (with a diary). This dataset can be used to analyse human movements, transitional movements, and postural changes based on a range of features.

Background & Summary

Inertial measurement units (IMUs) have seen increasing popularity as wearable sensors in the healthcare[1–3] and sports sectors[4–6]. In healthcare, wearable sensors offer a way to capture data about people's everyday activities easily and in an economical way, both within and outside clinical environments[7]. Mosenia et al.[8] noted that wearable sensors in health monitoring can reduce the costs of long-term care in hospitals. These sensors can be used in different types of movement analyses such as human posture classification[9,10], activity classification[11,12], gait analysis[13,14], transitional movement analysis[15,16], sleep monitoring[17,18] and falls detection[9,19].

While a number of studies investigate the use of a single wearable sensor (e.g. on the wrist or on the lower back), increasing the number of sensors can help with improving the accuracy of monitoring systems and capture a more complete view of the body's movements. Though multiple sensors increase the accuracy of human activity recognition[20–24] (HAR), putting on and wearing multiple sensors can be a tedious or laborious task for the wearer. There are also potential challenges with ensuring the sensors are placed in appropriate locations and orientations. One approach to improving the process of wearing multiple sensors is to embed these sensors onto clothing[25–28]. Most previous studies have experimented with tight-fitting clothes[29–32] to help ensure the sensors stay close to the limbs without moving during data collection. In a healthcare context where tight-fitting clothes may not be appropriate nor desirable, attaching multiple sensors to loose-fitting, everyday clothing offers comfort and convenience[28,33,34], without the burden of needing to strap on sensors one-by-one and adjusting them. This research investigates sensors in loose-fitting, everyday clothing so the wearer can have them on for longer periods in a comfortable way.

There are already publicly-available databases of Human Activity Recognition (HAR)-related wearable sensor data. These include data collected from a waist-mounted smartphone with accelerometer and gyroscope sensors[35–38], a waist-mounted IMU[39], an ankle-mounted IMU with a stretch sensor[40] and 17 Magnetic, Angular Rate, and Gravity (MARG) sensors mounted on the head, shoulders, chest, arms, forearms, wrist, waist, thighs, shanks, and feet[41]. Further, databases are available for gait analyses such as Luo et al.'s[42] study with 6 body-worn IMUs, Lencioni et al.'s[43] study using camera motion, force plates and electromyography (EMG) and Loose et al.'s[44] study using Xsens sensors on both feet, shanks, thighs and pelvis.

The present database has loose clothing-embedded IMU data from the lower body, alongside video recordings and diaries as ground truth data. The data were recorded from semi-natural activities i.e. a video-recorded pre-defined set of activities (standing, sitting, lying down, sitting with legs outstretched, walking, climbing up and down stairs - approximately 20 minutes in total) and participants' usual day-to day activities during the rest of the day along with diary data for 5 to 8 hours. Data were collected from five healthy participants for between 1-4 days per person, for a total of 15 participant-days' of data. To our knowledge this is the first published database consisting of data collected from loose clothing-embedded IMUs. This dataset is likely to be of interest to researchers studying human postures and movements in natural settings, particularly that the sensors are worn unobtrusively in loose-clothing rather than on the body and also that the data includes measurements of the waist, thigh and ankle on both the left and right sides.

We have previously published a paper[45] based on this dataset where a posture classifier was implemented using a single feature (the inclination angle estimated from the accelerometer data) from three sensors (waist, thigh and ankle). Four postures (standing, sitting, lying down and sitting on the floor with legs outstretched) were classified with a high level of accuracy, demonstrating that the data from the sensors embedded in clothing can be used productively in posture classification. With this earlier paper, we published some of the processed data, specifically the inclination angles from a subset of the sensors. The aim of the present paper is to make available a more detailed dataset from the clothing on the lower-body, which includes data from six IMUs (accelerometers, gyroscopes, and magnetometers) and from a wrist-worn sensor, along with videos, diaries, and annotations of the activities, which we anticipate will enable further research and analysis.

Methods

Materials

The data[46] presented in this paper were collected as part of a larger dataset from sensors in the clothing on both the upper and lower-body, as well as a wrist-worn sensor (not attached to clothing). Here, we present the data from the lower body only; we intend to publish the data from the upper-body at a later date.

The sensing system in the clothing consisted of 12 IMUs (based around the Bosch Sensortec BMI160 smart IMU), all using a differential serial bus, connected via flat ribbon cable forming a "sensor string". The 12 bespoke sensors were approximately 15×12×7 mm each (see Figure 1 (b)) and weighed 18g in total while the inter-connecting cables weighed 146g. The string was connected to a Raspberry Pi where the data were stored. The battery pack enabled continuous mobile data collection for more than 12 hours (10000 mAh output : 5V, 2.1 A). Data were sampled at 50 Hz. The range of the accelerometers was +/- 16 g with 12-bit resolution. The BMI160 IMU includes a gyroscope with a range of 1000 degrees per second and magnetometer, which were also recorded along with accelerometer readings. Since accelerometer, magnetometer, and gyroscope data were all recorded from each sensor, a time division multiplexing bus protocol running at 500K baud was used.

The 12 IMUs were positioned in the clothing so that there were three sensors along the lateral side of the upper limbs (wrist, upper arm, and shoulder/neck) and lower body (ankle, thigh, waist), on both the left and right sides (Figure 1). To attach the sensors to the clothes, the sensors were taped securely along the seams of the clothes in the chosen positions as shown in Figure 1 (b) and cotton bias binding was taped on top of the sensor string using double-sided tape for fabric. In this way, the sensors were not outwardly visible and also not in contact with the skin. That helped to make the outfit with sensors more comfortable for the wearer. In addition to the clothing worn sensors, an Actigraph, device was strapped onto the wrist of the dominant hand of the participant as a reference, body-worn sensor. The Actigraph sampling rate was also set to 50 Hz.

Data Collection Procedure

Five healthy participants (age range: 28-48 years old; 3 males and 2 females) took part in this study. Each person selected a pair of trousers and a hoodie jacket in their usual size, and the researcher attached the sensors to the clothes. Four participants wore cotton-blend fleece jogging trousers, and one wore loose cotton slacks. (One of the

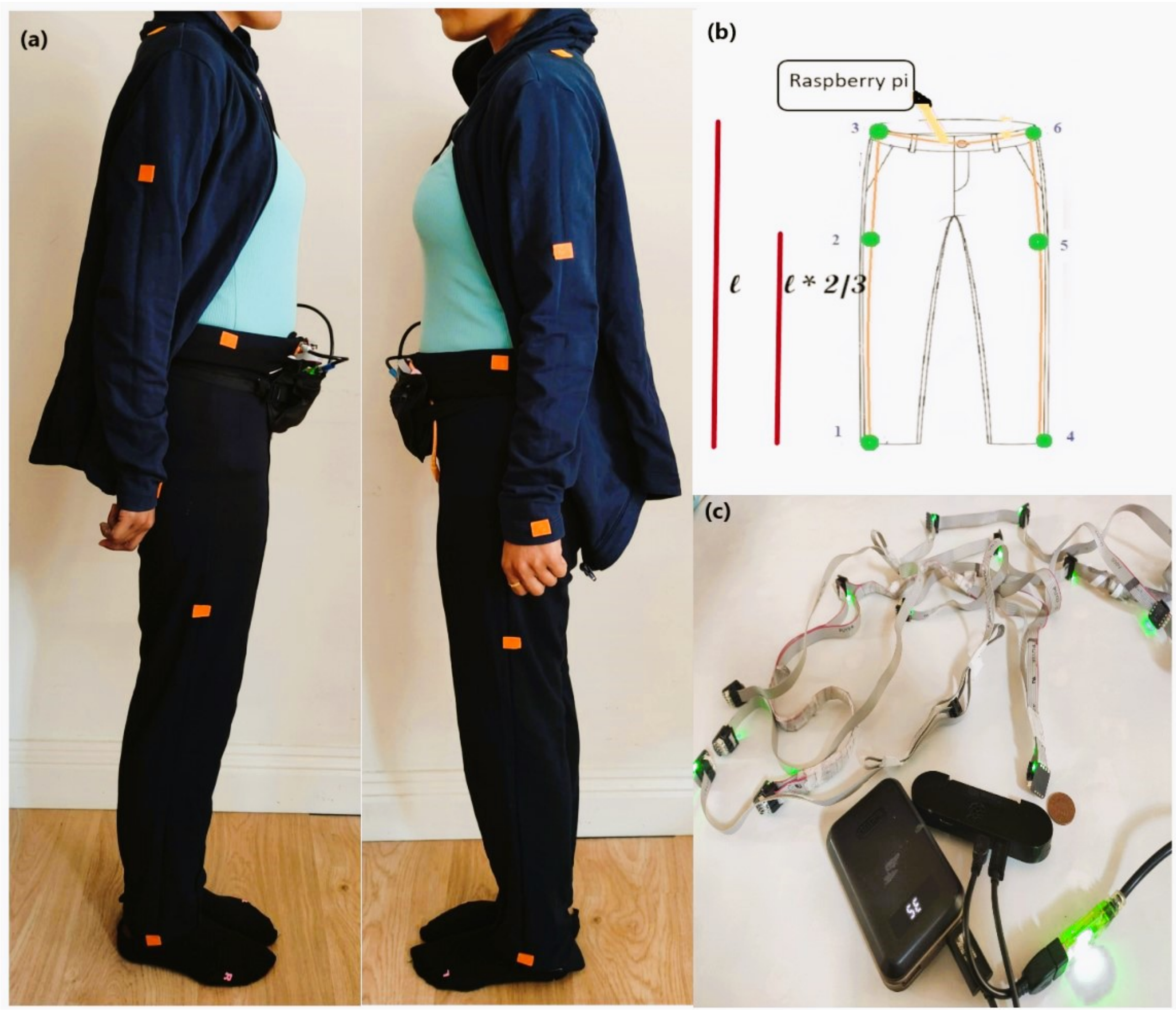

Figure 1. Sensor placement on the clothing (a) and set up of the sensor strings (b). The sensor placements are indicated with stickers in (a). The measurements used to position the sensors are shown in (b), where l is the leg length. Ankle sensors were placed near the hem of the trousers (sensors 1 and 4 as marked in Figure 1 (b)). The thigh sensors were placed at $l \times 2/3$ (two-thirds of l) above the ankle sensor (sensors 2 and 5 as marked in Figure 1 (b)). The IMUs connected to the battery-powered Raspberry Pi are shown in (c), where a one penny coin is included for scale. The present paper focuses on only the data from the 6 sensors on the lower-body.

male participant's trousers were baggy at the thigh, compared to the other participants' trousers.) Participants were asked to wear the clothes over multiple days for 5-8 hours per day of data collection. The protocol was approved by the ethics committee of the School of Biological Sciences, University of Reading, UK (SBS 19- 20 31 and SBS 21- 22 18). The study was conducted in accordance with this approved protocol and the relevant guidelines and regulations. All participants provided written informed consent to take part in the study and to have the data published openly.

The Raspberry Pi and the battery pack were kept in a pouch on the waist of the participant. Once the Raspberry Pi was powered on, it started recording data. Further, to check that the data were being recorded, the Raspberry Pi could be accessed with a mobile phone via SSH (secure shell). Figure 1 (a) shows a participant with the clothing-embedded sensors with the the Raspberry Pi on the waist. The sensors were not visible from the outside of the clothing, other than the waist bag with the Raspberry Pi.

On each day of data collection, participants were asked to perform a set of predefined activities, and these activities were video-recorded to provide a ground truth. Ground truthed data were recorded for the following set of activities (in order):

1. Standing still for 2 minutes
2. Sitting (on a chair) for 2 minutes
3. 5 cycles of raising the legs while sitting down
4. 5 Sitting-to-standing cycles
5. Walking back and forth for 2 minutes
6. Climbing up and down stairs for 2 minutes
7. Lying down for 1-2 minutes
8. Sitting on the floor with legs outstretched for 1-2 minutes

After the predefined activities, the participants were asked to continue with their usual activities for the rest of the day (5 to 8 hours). During that time, the participants were requested to keep a diary of their activities and the times of those activities. This data repository consists of data from 15 days across five participants (see Table 1), with each participant contributing between 1 and 4 days' of data.

Data Workflow

Data Storing and Decoding

Data from the IMUs were serialised onto a twisted pair RS423 bus using 'base64' and saved on the Raspberry Pi through the serial port. Once a participant had completed their part in the study, these files were transferred to a PC, decompressed and analysed in MATLAB. Following a data cleaning and alignment process the data were saved as MATLAB 'MAT' files.

Data Cleaning

There were some signal losses owing to power supply issues during the data collection. Those points were identified by synchronising the dominant hand's 'wrist' clothing-sensor data with the Actigraph data and replacing missing segments with 0s.

	Day (name)	Activities in ground truth video									Start time	End time	Duration	Notes
		Standing	Sitting	Walking	Climbing up stairs	Climbing down stairs	5 leg raises	5 sit-to stands	Lying down	Sitting on the floor				
P1	Day 1 (P1D1)	✓	✓	✓	✓	✓	✓	✓	✓	✓	09:40	18:20	8 h 40 m	*Jogging trousers (baggy)*
	Day 2 (P1D2)	✓	✓	✓	✓	✓	✓	✓	✓	✓	11:15	19:20	8 h 05 m	
	Day 3 (P1D3)	✓	✓	✓	✓	✓	✓	✓	✓	✓	11:30	20:00	8 h 30 m	
P2	Day 1 (P2D1)	✓	✓	✓	✓	✓	✓	✓	✓	✓	10:50	17:10	6 h	*Loose cotton slacks* Weekend
	Day 2 (P2D2)	✓	✓	✓	✓	✓	✓	✓	✓	✓	12:15	18:45	6 h 30 m	Weekend 30 mins data missing
	Day 3 (P2D3)	✓	✓	✓	✓	✓	✓	✓	✓	✓	12:15	17:20	5 h	10 star jumps, 3 burpees 20 mins data missing
	Day 4 (P2D4)	✓	✓	✓	–	–	✓	✓	✓	✓	10:10	15:50	∼6 h	one hour data missing
P3	Day 1 (P3D1)	✓	✓	✓	✓	✓	✓	✓	✓(1 min)	✓(1 min)	07:50	12:30	∼4 h	*Jogging trousers*
P4	Day 1 (P4D1)	✓	✓	✓	✓	✓	✓	✓	✓(1 min)	✓(1 min)	09:10	14:55	∼6 h	*Jogging trousers*
	Day 2 (P4D2)	✓	✓	✓	✓	✓	✓	✓	✓(1 min)	✓(1 min)	09:40	16:56	6 h 30 m	
	Day 3 (P4D3)	✓	✓	✓	✓	✓	✓	✓	✓(1 min)	✓(1 min)	08:40	15:51	7 h	
P5	Day 1 (P5D1)	✓	✓	✓	✓	✓	✓	✓	✓	✓	14:00	18:40	6 h	*Jogging trousers*
	Day 2 (P5D2)	✓	✓	✓	✓	✓	✓	✓	✓	✓	14:00	19:10	5 h	
	Day 3 (P5D3)	✓	✓	✓	✓	✓	✓	✓	✓	✓	10:20	16:10	6 h	
	Day 4 (P5D4)	✓	✓	✓	✓	✓	✓	✓	✓	✓	10:22	16:10	∼6 h	

Table 1. Data catalogue. There are two minutes of data for standing, sitting, walking, climbing up/ down stairs , lying down and sitting on the floor (marked with a '✓') unless otherwise indicated ('−' indicates missing data). The start time and the end time of the data collection at the end of each day are given in the table, along with special notes such as whether the data were collected on a weekend, if special activities were performed, and which type of trousers they were wearing.

Pre-processing

All sensors used to collect data were individually calibrated against the magnitude and direction of the gravity vector so that a homogeneous transform matrix for each sensor could be calculated. This matrix then allowed corrections for scaling and axis orthogonality errors for each sensor.

Data were then processed to align the sensors to each limb as the orientation of the sensors inside the clothing was uncertain. Two rotation transforms were calculated to orient the data from each sensor relative to the presumed axis of the limb and then to the principal plane of movement of that limb. Thus the first rotation changes the data from the sensor frame $\{S\}$ to an intermediate frame $\{I\}$ and the second rotation changes the data from the intermediate frame to the final frame $\{F\}$.

The first rotation was applied to align the z-axis of the sensor to the the direction of gravity (superior-inferior). Following application of this rotation to the data, the z-axis of the intermediate frame $\{I\}$ was closely aligned with the gravity vector $\underline{\mathbf{g}}$. A period when the participant was standing still and the limb could be assumed to be vertical was chosen from the data and m points were sampled. The rotation matrix ${}^{I}_{S}R$ was calculated by determining an angle and axis for the rotation. (Note the notation here indicates that vectors in the $\{S\}$ frame were, after multiplication by ${}^{I}_{S}R$, the same vectors but now expressed in the intermediate $\{I\}$ frame).

Since there is no movement during this 'standing still' period, the sensors collected m data vectors that represent

${}^{S}\underline{\mathbf{g}} \simeq {}^{S}\underline{\mathbf{a}}_k$ where $1 \leq k \leq m$, i.e. the coordinates of the gravity vector in the sensor frame $\{S\}$. The magnitude of this vector should be approximately 9.81 ms^{-2} if the sensors are calibrated in metric units or 1 if calibrated in gravitational units. For convenience gravitational units are assumed for this section. Equation 1 calculates the average value of acceleration during period m from the individual measurements $a_{j,k}$

$$ {}^{S}\underline{\mathbf{a}} = \begin{bmatrix} {}^{S}a_1 & {}^{S}a_2 & {}^{S}a_3 \end{bmatrix}^T \quad \text{where} \quad {}^{S}a_j = \frac{1}{m}\sum_{k=1}^{m} a_{j,k} \quad \text{for} \quad j = 1,2,3 \quad \text{referring to the x, y and z axes} \tag{1} $$

This estimate can be readily converted to a unit vector that approximates ${}^{S}\underline{\mathbf{g}}$ in gravitational units using the 'hat' notation in equation 2.

$$ {}^{S}\underline{\mathbf{g}} \simeq {}^{S}\underline{\hat{\mathbf{a}}} = {}^{S}\underline{\mathbf{a}}/|\underline{\mathbf{a}}|, \quad \text{where} \quad |\underline{\mathbf{a}}| = \sqrt{a_1^2 + a_2^2 + a_3^2} \tag{2} $$

The first rotation converted ${}^{S}\underline{\mathbf{g}}$ to ${}^{I}\underline{\mathbf{g}}$ where it was assumed that ${}^{S}\underline{\mathbf{g}} \simeq {}^{S}\underline{\mathbf{a}}$. This was achieved by using the basis vector for the sensor z-axis ${}^{S}\underline{\hat{\mathbf{z}}} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^T$.

The axis of rotation $\underline{\mathbf{r_1}}$ was chosen to be perpendicular to both ${}^{S}\underline{\mathbf{a}}$ and ${}^{I}\underline{\hat{\mathbf{z}}}$ so could be estimated as

$$ \underline{\mathbf{r_1}} = {}^{S}\underline{\mathbf{a}} \times {}^{S}\underline{\hat{\mathbf{z}}} $$

($\underline{\mathbf{r_1}}$ has the same elements in both the $\{S\}$ and the $\{I\}$ coordinate frames)

To work correctly as an angle axis representation $\underline{\mathbf{r_1}}$ should be redefined to be a unit vector and this was done using equation 2.

The angle of the rotation was estimated from the dot product between ${}^{S}\underline{\mathbf{a}}$ and ${}^{S}\underline{\hat{\mathbf{z}}}$ since the definition of the dot product is

$$ {}^{S}\underline{\mathbf{a}} \cdot {}^{S}\underline{\hat{\mathbf{z}}} = |{}^{S}\underline{\mathbf{a}}| \cos(\theta_1) $$

If ${}^{S}\underline{\hat{\mathbf{a}}}$ is the unit vector aligned with ${}^{S}\underline{\mathbf{a}}$, then θ_1 could be computed simply as

$$ \theta_1 = \mathrm{acos}({}^{S}\underline{\hat{\mathbf{a}}} \cdot {}^{S}\underline{\hat{\mathbf{z}}}) $$

Both the angle and the axis were then available to compute the rotational transform using Rodrigues' formula as suggested by Chakraborty et al.[47] One form of Rodrigues' equation is shown in Equation 3 where K is a skew symmetric matrix derived from $\underline{\mathbf{r}}_1$. This 'K' (Equation 3) can be expressed with the elements of the $\underline{\mathbf{r}}_1$.

$$ {}^{I}_{S}R = I + \sin\theta_1 K + (1 - \cos\theta_1)K^2 \tag{3} $$

where $K = \begin{bmatrix} 0 & -r_1(3) & r_1(2) \\ r_1(3) & 0 & -r_1(1) \\ -r_1(2) & r_1(1) & 0 \end{bmatrix}$ and I is the 3×3 identity matrix.

The first rotation matrix was thus calculated from equation 3 using the data from the individual sensor accelerometers. Thereafter the same rotational matrix was then applied to the gyroscope and magnetometer data and the data from the sensors converted to this intermediate frame.

After applying the first rotation, any movements of the limb in the sagittal plane can be used to reorientate the x and y axes to the final coordinate frame $\{F\}$. The z-axis remains the same for both the intermediate $\{I\}$ and the final $\{F\}$ coordinate frames. The concept was to choose the direction of the lowest principal component of acceleration as the direction for the final x-axis.

For this paper 'sitting to stand', 'walking' and 'leg raising while seated' were selected as movements that happen in the sagittal plane from the perspectives of the waist, thigh and ankle respectively. Data for each of these segments, once converted to the intermediate frame, was selected to define the second rotation from the intermediate to the final coordinate frame.

The second rotation was computed and applied to make sure that the sagittal plane motions (i.e. sitting to stand, walking and leg raising while seated) would be be in the y-z plane of the final coordinate frame such that the y-axis aligns with the anterior-posterior direction in the sagittal plane and the x-axis with the medial-lateral direction perpendicular to the sagittal plane.

Chakraborty et al.[47] defined the plane-of-motion to be a plane perpendicular to the direction of minimum acceleration. Alternative methods to identify the plane of principal movement are possible, for example identifying a unit vector that aligns with any reasonably large angular velocity. However the preference in this case was to use the same IMU sensor, the accelerometer, to estimate both rotational transforms. A suitable data segments with movements in the sagittal plane were selected from the accelerometer for each IMU sensor. The eigenvectors of the covariance matrix of the centred data segment gives direction of maximum and minimum accelerations that align with the x and y axis of the final frame. These Eigenvectors are known to be orthogonal and can be readily computed either directly as Eigenvectors or from the singular value decomposition of the segmented data.

The second rotation occurs around the z-axis of the intermediate frame, which will also become the z-axis of the final frame. The direction of the vector ${}^{I}\underline{\hat{\mathbf{m}}}$ corresponding to smallest singular value or smallest Eigenvalue was used to identify the axis orthogonal to the z-axis of the intermediate frame. This vector was assumed to be orthogonal to most movements in the sagittal plane.

After finding the axis of lowest principal component in the intermediate frame (${}^{I}\underline{\hat{\mathbf{m}}}$), the second axis (${}^{I}\underline{\hat{\mathbf{f}}}$) (forward-backward acceleration) was confirmed by using vector cross product in equation 4 so that it was perpendicular to the axis of minimum acceleration.

$$ {}^{I}\underline{\hat{\mathbf{f}}} = {}^{I}\underline{\hat{\mathbf{z}}} \times {}^{I}\underline{\hat{\mathbf{m}}} \quad \text{where} \quad {}^{I}\underline{\hat{\mathbf{m}}} = {}^{I}\underline{\mathbf{m}}/|\underline{\mathbf{m}}| \tag{4} $$

vectors $\underline{\mathbf{m}}, \underline{\mathbf{f}}$, and ${}^{I}\underline{\mathbf{z}}$ were then associated with the directions of the x y and z axis of the final frame respectively and used to calculate the final rotation matrix ${}^{F}_{I}R$.

By using Rodrigues' rotation formula again (as described in Equation 3), a second rotation was applied (using Equation 4 and Equation 5) so that the transformed y-axis is aligned with the anterior-posterior direction and the transformed x-axis is aligned with the medial-lateral direction perpendicular to the sagittal plane.

$$ \underline{\mathbf{r_2}} = {}^{I}\underline{\hat{\mathbf{f}}} \times {}^{I}\underline{\hat{\mathbf{y}}} \quad \text{where} \quad {}^{I}\underline{\hat{\mathbf{y}}} = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}^T \quad \text{and} \quad \theta_2 = \operatorname{acos}\left({}^{I}\underline{\hat{\mathbf{f}}} \cdot {}^{I}\underline{\hat{\mathbf{y}}}\right) \tag{5} $$

Annotation

To annotate the data, the videos were synchronised with the sensor data using ELAN software[48]. The start and end points for each different posture and activity were manually identified by the first author, and those segments were annotated and saved in a file.

Data Records

The final labelled dataset comprises 15 participant-days of data across the 5 participants, with 6 video-ground truthed activities per participant per day. The data are organised in folders with a naming convention of 'PXDY' where X is the participant ID and Y indicates the day of the data collection (e.g. P1D1- Participant 1 Day 1). Each folder contains 5 items. The detailed version of the folder structure is given in Figure 2.

The file "PXDY.MAT" loads all the pre-processed data (orientation corrected) from each position/sensor along with the annotations (groundTruth). All the variable names are given in Table 2.

The file "PXDYDiary.txt" has approximate start and end times for activities and a brief description of the activities. In addition to the diary entries, the file contains a description with details of the date, start and end times of the data collection and whether or not there are missing data (i.e. if there was a power failure).

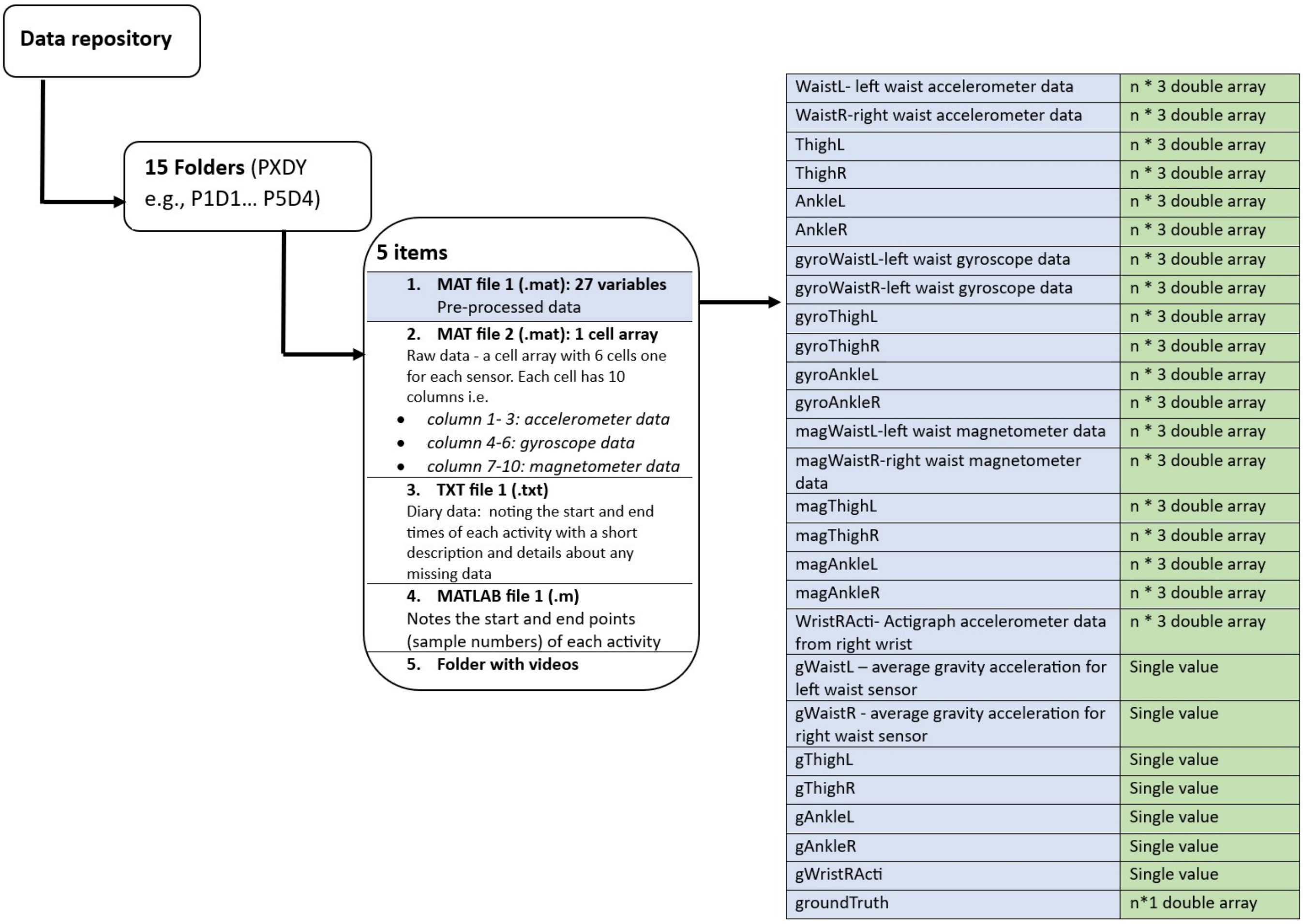

Figure 2. Data structure of the data repository. The repository contains 15 folders. Each folder contains 2 MAT files, 1 text file (diary data), 1 MATLAB file (video annotation file) and a folder with video files. The naming convention is 'PXDY' where X is the participant ID and Y is the day of the data collection (e.g. P1D1- Participant 1 Day 1).

Sensor	Side	Variable name			
		Accelerometer data	**Gyroscope data**	**Magnetometer data**	**Average gravity measured by the sensor**
Waist	Left	WaistL	gyroWaistL	magWaistL	gWaistL
	Right	WaistR	gyroWaistR	magWaistR	gWaistR
Thigh	Left	ThighL	gyroThightL	magThighL	gThighL
	Right	ThighR	gyroThightR	magThighR	gThighR
Ankle	Left	AnkleL	gyroAnkleL	magAnkleL	gAnkleL
	Right	AnkleR	gyroAnkleR	magAnkleR	gAnkleR
Actigraph Wrist-worn	Dominant hand	WristRActi	–	–	gWristRActi
–	–	groundTruth: 1- standing, 2- sitting, 3- lying down, 4- sitting on the floor, 5- walking, 6- climbing up stairs, 7- climbing down stairs, 8- sit-to-stands, 99- not defined			

Table 2. Variable names for a full-day dataset, including all the data from the pre-defined activities as well as the "rest of the day activities" of a participant. The Actigraph sensor has only accelerometer data (it does not have gyroscope and magnetometer data, as indicated by a '–'.)

Technical Validation

Visual Representation of Data

After applying the rotation matrices described in the "Pre-processing" section, the accelerometer signals were low-pass filtered with a second-order Butterworth filter with a 3 Hz cut-off. The filter was run on the data both forwards and backwards to minimise phase distortions. 'Standing' data before and after the orientation correction can be seen in Figure 3 a(i) - a(iii) and Figure 3 (b(i)-b(iii)) respectively. Those figures indicate that the z axis measures 1 g while the x and y axes measure 0 g as the person was not moving while standing upright.

The sensor angles with respect to the vertical axis are shown in Figure 3 c(i) - c(iii). These inclination angles were estimated from the inverse cosine of the acceleration due to gravity as measured on the z-axis. The inclination angles were 0° for all the sensors when the participant was in the upright 'standing still' position, as the sensors were all aligned with vertical through the first step in the alignment process. In comparison, when the participant was in the 'sitting' and 'sitting on the floor with legs outstretched' positions, the angle for the waist was about 25° - 40° as the participant was leaning forward/backward and the angle for the 'thigh' was approximately 90° as the thigh came to a horizontal position. These two postures can be distinguished by using the ankle sensor (sensor 1 in Figure 1 (b)). For 'sitting', the ankle was around 10° as the legs were inclined/reclined.When the participant was in the 'sitting on the floor' position it could be expected that ankle would be horizontal, however, the ankle angle was approximately 110°. This may be related to a shift in the clothing relative to the body, or possibly that the participant let their leg relax into a comfortable position, resulting in the toes facing outwards.

When calculating the sensor to vertical angle using the inverse cosine function (acos), the value ranges are limited from 0° to 180°. Hence, to calculate the angles for dynamic activities, rotation matrices were used in the calculation of the sensor to vertical angles. First, the inertial data from each sensor was used to estimate quaternions using Madgwick's algorithm[49] (`https://github.com/xioTechnologies/NGIMU-Software-Public`, accessed on 21 September 2021) and the sensor-to vertical angles were estimated by calculating the angle between the forward pointing vector and the gravity vector (as described in[50]). The angles based on the lower-body sensors for walking, climbing up stairs and down stairs are shown in Figure 4.

Usage Notes

Corresponding MATLAB scripts are provided to access, reuse and visualize the data. The MAT files are readable not only in MATLAB but also in Python with packages such as 'scipy'. Further, along with the data, video files and

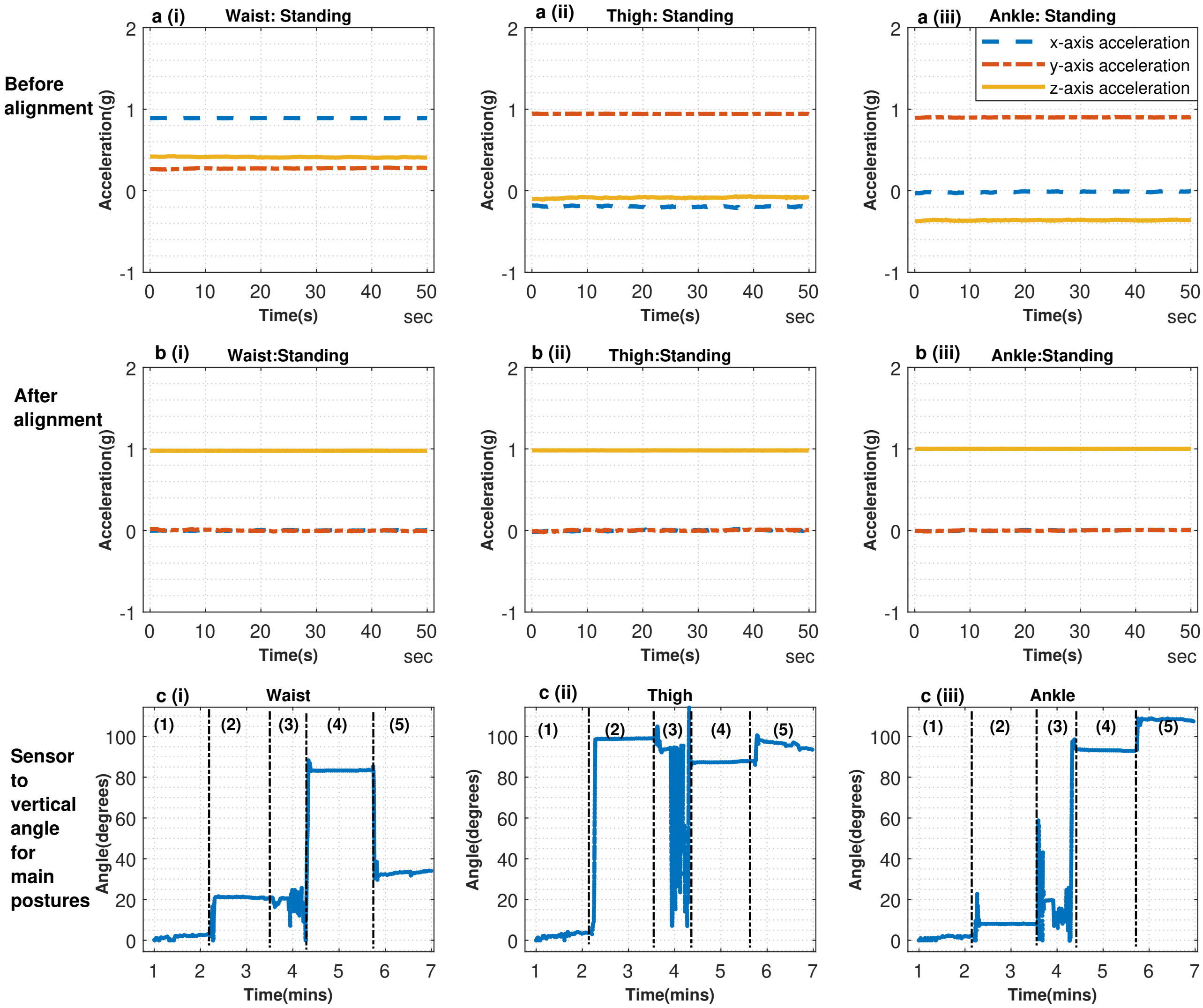

Figure 3. Orientation correction and sensor to vertical angles across different activities. The top plots(a(i)-a(iii)) indicate that the sensors were not initially aligned with gravity. The standing data, after applying the rotation matrices, are shown in the middle set of plots (b(i)-b(iii)). The z axis of each sensor measures the acceleration due to gravity (1 *g*) as it aligns with the superior-inferior axis while x and y axes measure 0 *g* as the person was standing still. The bottom plots c (i) - c (iii) show the angles of each sensor with respect to the vertical axis (superior-inferior) for (1) standing, (2) sitting, (3) leg raises while sitting and sit-to stands, (4) lying down and (5) sitting on the floor with legs outstretched. These data were from the right side from the Participant 1 Day 2 dataset.

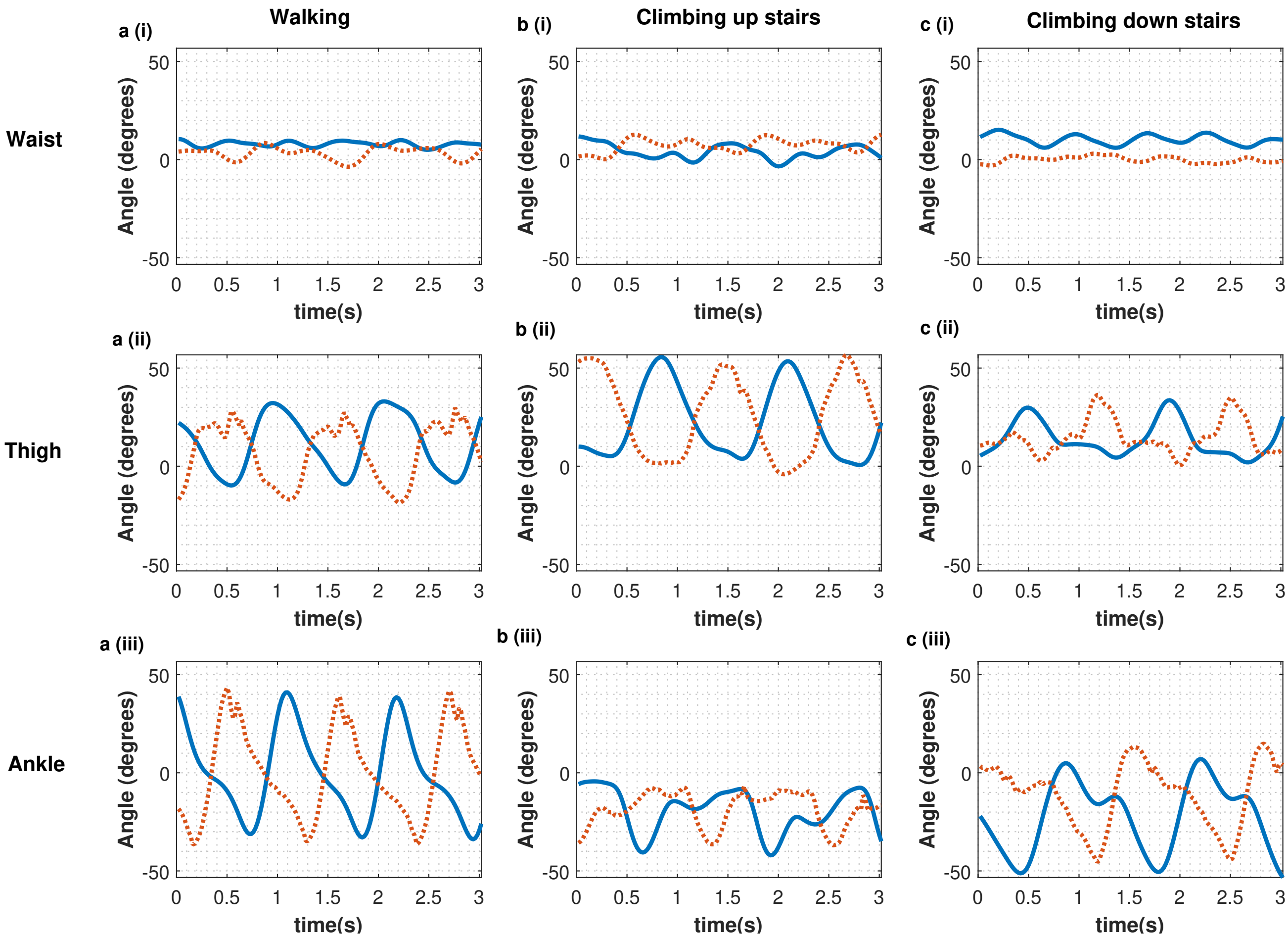

Figure 4. The "sensor to vertical" angles for the waist, thigh and ankle for different activities for Participant 1 Day 1. Angles for walking, climbing up and down stairs, from the right leg ('blue solid line') and the left leg ('red dotted line') are shown.

annotation files are given with a descriptive ‘readme’ file.

Code availability

Data and MATLAB scripts are available in figshare[46]. Further, csv files of the MATLAB variables and Python scripts to read the MAT files directly are also available in figshare[46].

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Author contributions statement

Conceptualisation, methodology, ALL; conducted the experiment(s), U.J; carried out the formal analysis of the results, ALL; investigation, ALL; resources, All; data curation, U.J.; writing—original draft preparation, U.J.; writing—review and editing, All; visualization, U.J.; supervision, W.S.H. and F.H.; All authors read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Chapter 5

Classification of Static Postures with Wearable Sensors Mounted on Loose Clothing

This chapter explains the way how the third aim of the research was achieved.

Chapter 3 concluded that the clothing-mounted sensor data correlate well with static postural data than the dynamic activity data. Hence, the aim of this chapter was to implement a posture classifier using the clothing-mounted sensor data (Chapter 4 : IMU Data From Loose Clothing Worn on the Lower Body During Everyday Activities data).

A classifier was implemented to recognise four main postures i.e. standing, sitting, lying down and sitting on the floor with legs outstretched, using a single feature (inclination angle) from three points of the body (waist, thigh and ankle). As the machine learning technique KNN algorithm was used. Using the classifier, the usual activities of the participants were analysed and interpreted the classifier output crosschecking the features and diary data of the participants.

Methodology, data analysis, discussion and conclusions are explained in detail on the attached paper titled "Classification of Static Postures with Wearable Sensors Mounted on Loose Clothing".

More figures that explain the feature selection procedure are listed as Appendix B.1 and B.2. Further, analyses carried out with all the participants are listed as Appendix B.3.

This analysis explained how different window sizes can be used in different scenarios in generating features to train classifiers. Further, it was shown that a posture classifier with higher accuracy (100%) can be implemented by using multiple clothing-mounted sensors with a minimum number of meaningful features.

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Classification of static postures with wearable sensors mounted on loose clothing

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Inertial Measurement Units (IMUs) are a potential way to monitor the mobility of people outside clinical or laboratory settings at an acceptable cost. To increase accuracy, multiple IMUs can be used. By embedding multiple sensors into everyday clothing, it is possible to simplify having to put on individual sensors, ensuring sensors are correctly located and oriented. This research demonstrates how clothing-mounted IMU readings can be used to identify 4 common postures: standing, sitting, lying down and sitting on the floor. Data were collected from 5 healthy adults, with each providing 1–4 days of data with approximately 5 h each day. Each day, participants performed a fixed set of activities that were video-recorded to provide a ground truth. This is an analysis of accelerometry data from 3 sensors incorporated into right trouser-leg at the waist, thigh and ankle. Data were classified as static/dynamic activities using a K-nearest neighbour (KNN) algorithm. For static activities, the inclination angles of the three sensors were estimated and used to train a second KNN classifier. For this highly-selected dataset (60000–70000 data points/posture), the static postures were classified with 100% accuracy, illustrating the potential for clothing-mounted sensors to be used in posture classification.

Maintaining correct posture in daily life is important and brings benefits such as maintaining good blood circulation and reducing the risk of chronic diseases[1,2]. When it comes to healthcare monitoring systems, for example in rehabilitation settings, it is important to monitor posture as well as the daily activity intensity of an individual[3,4]. Such monitoring allows both the person and the healthcare professional to assess the condition and the effects of any interventions, thereby helping to avoid injuries such as those arising from falls and to improve the physical condition of the patient[5]. For example, in stroke rehabilitation, posture evaluation can be done in the clinic using the Postural Assessment Scale for Stroke Patients (PASS)[6] and can be used to measure the progress of patients' recovery[7]. The availability of a PASS-like measurement with a finer graticule and greater accuracy can provide better insight into this recovery.

Mosenia et al.[8] noted posture identification and posture correction as some of the main applications of wearable medical sensors. Commercially-available wearable sensors are popular in activity monitoring in free-living environments as they can be used as self-monitoring devices. Consumer products typically contain all their sensors in a single housing designed to be worn in one body location, for example, on the wrist. However, research into activity-[4,9,10] and posture-classification[11–13] has demonstrated that the use of multiple sensors increases classification accuracy. Further, there is a trade-off between having multiple sensors with light-weight algorithms and having a single sensor to extract multiple heuristic features to feed into a complex algorithm.

For the end user, putting on multiple sensors can be a tedious or laborious task, and this can be exacerbated when the physical process of attaching the sensor to the body is difficult, for example due to motor impairment or due to a design requiring good manual dexterity. Furthermore, analysis of the sensor data can be complicated if sensors are incorrectly placed, or if they slip off the limb during the day. One approach to make it easier for the end user to wear multiple sensors is to embed the sensors into garments[13–15]. In 2002, Laerhoven et al.[16] emphasised the importance of mounting sensors into clothing. They claimed that as clothing gives a larger space to mount multiple miniaturised IMUs, clothing is an excellent platform to collect more data without disturbing the wearers. Most prior work on smart garments investigates tight-fitting garments in order to hold the sensors in-place close to the body. Our research investigates sensors in loose-fitting, everyday clothing that is likely to be more comfortable for the wearer, easier to don on and off and more appropriate for everyday use.

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This work is novel in a number of ways. Most prior work in smart garments investigates tight-fitting garments, whereas here we investigate loose clothing which is likely to be more comfortable for everyday use. Other studies investigating loose clothing have examined specific activities (shoulder movements[17]) or specific clothing items (hospital garments[18]), whereas here the sensors are embedded into participants' own everyday clothing and capture data relating to a range of everyday activities/postures. Our study was conducted in a semi-natural setting over an extended period (hours and days), compared with others[15,17–19] which look at shorter time periods (e.g. on the order of minutes) under controlled conditions. Finally, this study demonstrates that a single feature from each of multiple sensors is enough to achieve a high level of classification accuracy.

Related work

Work by Lyons et al.[12] describes a method of calculating the inclination angles of the thigh and trunk for different postures. Dual axis accelerometers were strapped onto the person over their clothing. Data analysis distinguished activities into dynamic and static activities based on the standard deviation of the magnitude of the thigh accelerometer data over a 1 second window. Lyons et al. used a pre-defined threshold value to assign the data into the two categories (static and dynamic)[12]. Vipul et al.[11] used both waist and thigh sensor data (right hand side) to classify data into dynamic and static activities. They investigated two features, the integral of the signal magnitude over 1 s windows and a continuous wavelet transform of the filtered raw acceleration. Fida et al.[20] described how the window sizes contribute in identifying static/ dynamic/ transition activities. Their conclusion was that larger window sizes (e.g. 1.5–3.0 s) gave higher accuracy in identifying long duration activities and smaller window sizes (e.g. 0.5 s), gave higher accuracy in identifying short duration activities such as transitions[20]. Fida et al. used a single triaxial accelerometer mounted on the waist and a feature vector consisting of 22 time-based components, including means, standard deviations, skewness, and kurtosis for all window sizes (0.5 s, 1s, 1.5 s and 3 s). Chong et al.[21] examined 206 time and frequency-based features with different types of classifiers (Artificial Neural Networks, Support Vector Machines and Random Forests(RF)) in activity classification with a single accelerometer mounted on the right hip. The study indicated that subsets from time-domain features are sufficient to classify accelerometry into activities even without analysing frequency domain features[21].

Other than the above mentioned studies with body-mounted sensors and smart-textile data, Chiuchisan et al.[18] used a pair of loose-fitting trousers with an Arduino Nano board with 2 inductive sensors and an IMU. The sensor was placed near the knee. From their data, they concluded that there was potential to use these data from loose-fitting trousers for identifying different movement patterns in clinical rehabilitation[18].

In addition to the studies based on data from the lower-body, data from the upper body has also been investigated in posture classification. Lin et al.[19] and Harms et al.[17] implemented posture classifiers with sensors mounted in loose-fitting jackets. The study conducted by Lin et al. was based on four low-cost strain sensors mounted on the shoulder, elbow, abdomen and waist[19]. They used Long Short-Term Memory (LSTM) networks in implementing three classifiers with their sensor output which was a single voltage value. First, they classified the data into three static postures (standing, sitting and lying) and two dynamic activities (walking and running). Secondly, they detected static postures with random arm movements and finally, they classified the data into sitting and two different slouch positions[19]. Harms et al. attached accelerometers onto the forearm and upper arm of a loose-fitting garment to classify the data into ten postures that are useful in shoulder and elbow rehabilitation. They implemented a simulation with a body model and corrected the orientation error based on empirical samples of data. Finally, they concluded that there was a possibility of increasing the classifier accuracy based on the correction of the simulation[17].

To perform posture classifications, both[11] and[12] calculate inclination angles of the waist and thigh sensors relative to the direction of gravity. Skach et al.[15] use woven pressure sensors on trousers to categorise postures. These sensors were near the person's thigh and buttocks during a set of video-recorded, controlled postures involving the thigh and shank (e.g. leg-crossing postures). They used a RF classifier to classify the data into postures[12] and[15] both relied on thigh data in posture classification.

In[11,12] the sensors were strapped onto the body over the clothing and in[15] the sensors were woven into the clothing. In our present study, the sensors were attached to the inside of loose clothing. Prior to the work reported here, an earlier study verified how well loose clothing-mounted sensor data correlated with body-worn sensor data[22] and concluded that clothing sensor data were reasonably correlated with body worn sensor data, especially with static postures. Hence, there is good potential of using clothing-mounted sensor data in activity/posture classification.

The above mentioned studies which used lower-body data in posture classification[11,20,21] used multiple features from each sensor to train the classifiers. Even though Lin et al.[19] used only a single feature from each sensor, they used an LSTM (deep learning approach) network in their study. Rather than using a deep learning approach which usually trains classifiers on the raw data, our study uses a machine learning approach with a meaningful single feature (inclination angle). As the inclination angles of body parts are used as the feature vector, the features can be easily represented by a stick figure for an intuitive interpretation of the classifier output. Vipul et al.[11] (waist and thigh) and Lyons et al.[12] (trunk and thigh) used two body-mounted sensors in their studies. However, an additional ankle sensor, as studied here, can improve classification accuracy as it helps to differentiate postures that depend on the lower leg. Further, Lyons et al. pre-defined threshold values for the inclination angles to classify the data into different postures, whereas the present study uses a machine-learning approach to define the classes, rather than hard coding the threshold values. See supplemental files for a table comparing prior studies with the present work.

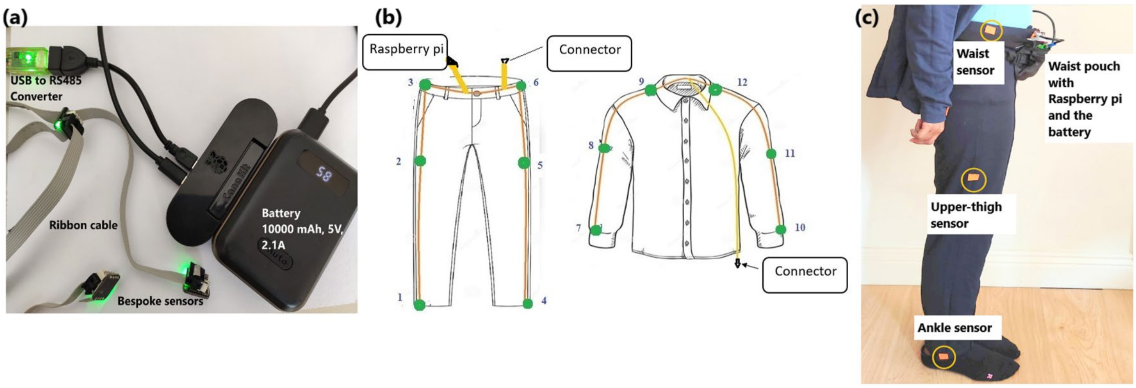

Figure 1. (**a**) Components of the sensor system. (**b**) Sensor placement on clothes. (**c**) Sensor placement on trousers. 12 IMUs are connected to a synchronous bus via ribbon cable. The sensors are connected to a Raspberry Pi via a USB to RS485 converter, and the Pi was powered by a battery pack. Lights on the sensors provided assurance of the sensors' operation but were not visible outside the clothing. The Pi and battery were worn in a waist-pouch attached with a belt, with 4-pin connectors connecting the bag components, the trousers and the top. The 12 sensors were sampled synchronously at 50Hz. Since accelerometer, magnetometer, and gyroscope data were all recorded from each sensor, this demanded a time division multiplexing bus protocol running at 500K baud.

Methodology

Materials. Our sensing system consisted of 12 IMUs (based on the Bosch Sensortec BMI160 smart IMU), all using a differential serial bus, connected using flat ribbon cable forming a *"sensor string"*. The 12 bespoke sensors were approximately 15×12×7 mm each (see Fig. 1a) and had a combined weight of 18g. The inter-connecting cables weighed 146 g. The sensor string was connected to a Raspberry Pi where the data were stored (Fig. 1a). A battery pack enabled continuous mobile data collection for more than 12 hours (10,000 mAh output : 5V, 2.1A). Data were sampled at 50 Hz. The range of the accelerometers was ± 16 g with 12-bit resolution. The BMI160 IMU includes a gyroscope and a magnetometer, which were also used to record data, alongside the accelerometers. The sensors use a time division multiple access (TDMA) based protocol, where each start-of-frame character allows the IMUs to trigger the acquisition of the next sample, thus resulting in a tightly-synchronised sensor network.

The 12 IMUs were positioned in the clothing so that there were sensors along the lateral side of the upper limbs (wrist, upper arm, and shoulder/neck) and lower body (ankle, thigh, waist), on both sides (Fig. 1b). To attach the sensors to the clothes, the sensors were taped securely along the inner seams of the clothes in the chosen position, and cotton bias binding was taped on top of the sensor string using double-sided tape for fabric. In this way, the sensors were not outwardly visible (see Fig. 1c) and also not in contact with the skin which helped to make the system more comfortable for the wearer.

Data collection procedure. Five healthy participants (age range: 28–48 years old; 3 males and 2 females) took part in the study. Each person selected a pair of trousers and a hoodie jacket in their usual size, and the researcher attached the sensors to the clothes. Four participants wore cotton-blend fleece jogging trousers, and one wore loose cotton slacks. Participants wore the clothes on three or four days (with the exception of 1 participant who was only able to take part for one day) for 5–8 hours per day of data collection. The Raspberry Pi and the battery pack were kept in a bag on the waist of each participant as shown in Fig. 1c.

On each day of data collection, participants were asked to perform a set of predefined activities which were videoed to provide a ground truth. Thereafter they continued with their usual activities for the rest of the day. The ground truthed activities comprised two minutes of each of the following: (1) Standing still, (2) Sitting on a chair, (3) Lying on their back (supine position), (4) Sitting on the floor with legs outstretched, (5) Walking back and forth and (6) Going up and down stairs. For the rest of the day's activities, participants were requested to keep a diary of their activities.

The study was reviewed by the research ethics committee of the School of Biological Sciences, University of Reading, UK and given a favourable ethical opinion for conduct (reference: SBS-19-20 31). The study was conducted in accordance with this approved protocol and the relevant guidelines and regulations. All participants provided written informed consent.

Data processing work flow. In this section, we provide an overview of the data processing workflow. Further elaboration of particular steps in the workflow are in the subsections that follow.

Data from the 12 IMUs were logged onto the Raspberry Pi. Once the data collection was completed, the data were transferred to a PC and analysed using MATLAB. Although the IMUs provide accelerometer, gyroscope and magnetometer readings, the main focus of this analysis was the accelerometer data from the right side of the lower body (sensors 1, 2 and 3 as shown in Fig. 1b).

As the placement and orientation of the sensors relative to the body could vary slightly from day to day depending on the fit of the clothing, each day's data were pre-processed to align all sensors to a common

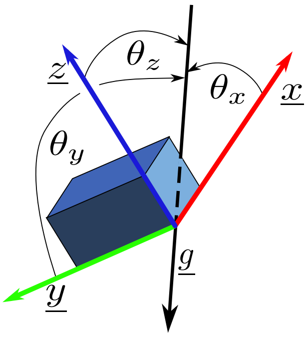

Figure 2. Orientation of the IMU with respect to a vertical axis represented by gravity (**g**) can be defined as the cosines of angles θ_x, θ_y and θ_z.

coordinate frame such that the z-axis is aligned with the direction of gravity (Section 'Data pre-processing'). The data were also low-pass filtered to remove noise. From the filtered data, the sensor-to-vertical angle was estimated as described in Section 'Calculating sensor to vertical axis angles'.

A classifier was implemented to first classify the data into "static postures" or "dynamic movements" (Section 'Classifying static and dynamic activities (classifier 1)'). For data classified as "static postures", a second classifier was implemented to classify the data into four specific postures (i.e. standing, sitting on a chair, lying down, sitting with legs outstretched) (Section 'Classifying postures (classifier 2)').

Data pre-processing. *Data rotations.* With the sensors embedded in the clothing, the initial orientation of the sensor relative to the limb and to the world is unknown. Hence, we apply a rotation to the accelerometer data to align the sensor's z-axis with the direction of gravity. This rotation can be computed easily using Rodrigues' rotation formula[23] by identifying the axis for rotation as being perpendicular to both the gravity vector and the z-axis. This is identified as the cross product between the gravity vector and the z-axis and the angle for rotation is the angle between these two vectors. To do this, we find a segment of 'standing still' data and assume that the limbs are all vertical and the only accelerations are those due to gravity[22].

There is a possibility of having a second rotation that transforms the data so that the transformed y-axis is aligned with the anterior-posterior direction and the transformed x-axis is aligned with the medial-lateral direction perpendicular to the sagittal plane. The rotation matrix can be estimated by finding suitable segments of data where there is rotation in the sagittal plane (e.g. walking, leg raising, sitting-to stand). However, the second rotation was not required for the present analysis.

Filtering. Accelerometer signals were then low-pass filtered with a second-order Butterworth filter with a 3 Hz cut-off as suggested in[12]. The filter was run on the data both forwards and backwards to minimise phase distortions at the expense of causality.

Calculating sensor to vertical axis angles. Estimation of the orientation of a wearable inertial sensor from gyroscope, accelerometer and magnetometer measurements is complex, with a variety of approaches[24]. A common simplification is to estimate the sensor inclination angle with respect to the local gravity vector. This estimate can be made with only the accelerometer, but additional information from the gyroscope and magnetometer can be used to improve the estimate of the sensor inclination angle.

The acceleration measured by the accelerometer can be considered as a baseline gravitational acceleration **g** with a 'dynamic' acceleration **a** added. Thus the accelerometer sensor measurement is $\left[s_x,\ s_y,\ s_z\right]^T = {}^S\mathbf{g} + {}^S\mathbf{a}$, where the two accleration components are measured in the sensor frame $\{S\}$[25]. It is fair to assume that the magnitude of gravity is fixed in a world frame $\{W\}$, i.e. ${}^W\mathbf{g} \approx \begin{bmatrix}0 & 0 & 9.8m/s^2\end{bmatrix}^T$ and that for typical human movement the 'dynamic' acceleration will have a zero mean if estimated over a sufficiently long time window.

When subjected only to gravitational acceleration (that is, $\mathbf{a} = 0$) the sensor will measure the components of **g** in the world frame along its three sensor frame axes as shown in Fig. 2. That is to say that the sensor will measure just the gravity vector so $\mathbf{g} = |\mathbf{g}| \begin{bmatrix}\cos\theta_x & \cos\theta_y & \cos\theta_z\end{bmatrix}^T$.

Three methods are outlined to recover the sensor orientation with respect to gravity and hence the angle of a limb with respect to a vertical axis. The first of these (the arccos method), was used for subsequent results.

Estimating sensor inclination angle with arccos. If the sensor consists of only a 3-axis accelerometer, and we assume one of the sensor axes is aligned with the limb (it was assumed the sensor z-axis aligns with limb), then the inclination of the sensor is simply calculated as the arccos of the relevant sensor component on the assumption that there is no dynamic (non gravitational) acceleration (Eq. 1).

$$\theta_z = \arccos\left(\frac{s_z}{|\mathbf{g}|}\right) \tag{1}$$

Estimating sensor inclination angle with atan2. If the sensor is well positioned on the limb so that it is aligned with an anatomical plane (for example the y-axis lies in the sagittal plane with the x-axis perpendicular to the plane), then an atan2 function can give information relating to the limb angle (Eq. (2)). Using the atan2 function would allow a direct distinction of whether the person was leaning forward or backward, or lying in a supine position or prone position.

$$\theta_z = \text{atan2}\left(s_y, s_z\right) \tag{2}$$

This method confines the result to be in the $y - z$ plane that may move with respect to the sagittal plane if the sensor is able to twist on the clothing, hence was not used for this analysis.

Estimating sensor inclination angle with a rotation matrix. Sensor fusion algorithms such as MARG (Magnetic, Angular Rate, and Gravity) algorithms attempt to calculate an orientation matrix or quaternion relating the sensor frame $\{S\}$ to the world frame $\{W\}$, for example Mahony et al.[26], Madgwick et al.[27] and Sabatini[28]. The orientation of the sensor is then simply the relevant column of the orientation matrix since the gravity vector would align with a world coordinate frame. A problem is that the sensor is defined with respect to a global coordinate frame (e.g. East, North, Up). The 'horizontal' (East and North) axis estimates tends to be poor as they suffer from problems such as integration drift or local distortions in the earth magnetic field. It then becomes difficult to align the global frame with the sagittal plane of the individual, hence the arccos method was considered the simplest and easiest method to use for this work.

Classifying static and dynamic activities (Classifier 1). *Activity extraction.* The ground truth videos were synchronised with the sensor data using ELAN software[29]. The start and end points for each of the four static postures (standing, sitting, sitting on the floor with legs outstretched and lying down) and dynamic activities (walking, going up and down stairs) were manually identified and annotated by the first author, and those segments of the data were extracted for analysis. In this way the transitions in-between the activities were deliberately not included in the analysis. For postures and dynamic activities, data segments of approximately 90 s were extracted from longer continuous data segments. The final labelled dataset comprised data collected over 15 participant-days across the 5 participants, with 6 video ground truthed activities per participant per day. Roughly 405,000 (= 6 activities $\times$ 90 s $\times$ 50 Hz $\times$ 15 days) data-points were used in the training process (data collection frequency was 50 Hz).

Static postures versus dynamic movements. The main intention of this study was to analyse the postures of the participants, hence the activities were first categorised into two classes: static postures and dynamic movements. We extracted three features which were moving standard deviation of the vertical axis of the 'Thigh' data and moving standard deviation of the magnitude of the 'Thigh' and of the 'Waist' data, according to the literature ([11,12,15,21]). Instead of defining threshold values to distinguish static vs dynamic activities as in[11,12], we compared the accuracy of classifiers in distinguishing the two classes with different combinations of features and with five different window sizes (0.5 s, 1 s, 1.5 s, 2 s and 3 s). The annotation files described in section 'Classifying static and dynamic activities (classifier 1)' were used to provide the ground truth for the classifier. The activities were labelled as static (standing still, sitting on a chair, lying on their back, sitting on the floor with legs outstretched) or dynamic (walking back and forth, going up and down stairs). Those labels, along with the three features, were then passed into MATLAB's 'Classification Learner App'. The data were trained with all the options available in MATLAB's 'Classification Learner App'. These included 'Discriminant analysis', 'Naive Bayes', 'Decision trees', 'Support vector machines', 'K-nearest neighbour (KNN)' and 'Ensemble classifiers'. It was found that the 'Weighted KNN' classifier achieved the highest accuracy in this classifier (Classifier 1). As such Weighted KNNs which use an Euclidean distance metric with 10 neighbours were used, and a further comparison to study the accuracy of the classifier with different combinations of features and window sizes was conducted. To evaluate the model, 5-fold cross-validation and leave-one-subject-out methods were used.

When analysing the data from the non-ground truthed (i.e. the rest of the day's) activities, 'Classifier 1' outputs were checked for both the left and right legs separately, to account for the possibility that a person could be moving one leg while still being considered to be in a 'static' posture. Data were not classified as dynamic unless the 'Classifier 1' output indicated that there was dynamic movement in both legs.

Classifying postures (classifier 2). For each sensor, the accelerometer data were further filtered by taking the moving mean over a 1s window. The filtered acceleration values were used to calculate the inclination angle of each sensor using Eq. (1), where s_z is the moving mean of the acceleration in the z-axis and g is the magnitude of the moving mean of the acceleration when the participant is 'standing still'.

The inclination angles of the three lower body sensors (Waist, Thigh and Ankle) were extracted and, along with their annotations, were fed into MATLAB's 'Classification Learner App' to train a KNN classifier (Classifier 2). As mentioned earlier in "Static postures versus dynamic movements" section all the options in the 'Classification Learner App' were checked with the data and the classifier type which gave the highest accuracy was selected. The selected KNN classifier was a 'Weighted' KNN which uses a 'Euclidean' distance metric with 10 neighbours. To evaluate the model, 5-fold cross-validation and leave-one-subject-out cross validation were used.

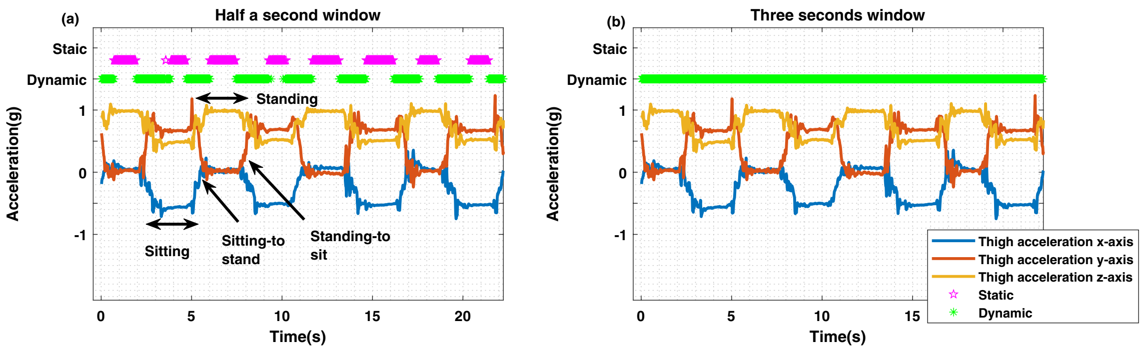

Figure 3. Classification outputs for a 0.5 s window (left) compared with a 3 s window (right), trained using the standard deviation of the magnitude of the thigh data. The plots show the 3-axes of acceleration from a sensor on the thigh as one participant performs 4 sit-to-stand cycles. The classifier outputs are shown at the top of each plot. For a 0.5 s window, the classifier identifies periods of static postures and dynamic movements within each sit-to-stand movement. In contrast, for a 3 s window, the whole segment is classified as a dynamic movement.

Results and discussion

Classification of static and dynamic activities. The confusion matrices were examined for different combinations of features ((i) moving standard deviation of the magnitude of the thigh data alone, (ii) moving standard deviation of the magnitude of the thigh data combined with the moving standard deviation of the vertical axis of the thigh data, and (iii) the previous two features combined with the moving standard deviation of the magnitude of the waist data) and window sizes (0.5 s, 1 s, 1.5 s, 2 s and 3 s). They showed that the false positive and false negative values were gradually decreased with additional features when the windows were 0.5 s and 1 s. However, when the windows were 1.5 s, 2 s and 3 s, the classification accuracies for all combinations of features were 100% with the given training dataset.

Further, it was noted that the moving standard deviation of the magnitude of the waist data and of the thigh data were strongly correlated. As the thigh can capture more information than the waist in postural changes, only the standard deviation of the magnitude of thigh data was selected to train Classifier 1.

It was noted that for the static postures, the moving standard deviation did not surpass ≈ 0.005 g, whereas for dynamic activities it was consistently above 0.1 g.

Figure 3 illustrates how the classification output varies with window size, over four sit-to-stand cycles. With window sizes of 0.5 s (left), 1 s, 1.5 s and 2 s, the classifiers identified periods of sitting and standing as static postures, and transitions between sitting and standing as dynamic movements. With a window size of 3 s (right), however, the classifier identified the whole segment where the participant was performing sit-to stands as a dynamic movement segment.

For this paper, the intention was to analyse the participants' postural changes throughout the day and estimate the proportion of active (dynamic) movements relative to passive postures. Hence, the transition movements were not of primary interest, rather the focus was on identifying longer segments of static and dynamic activities. Therefore, the standard deviation of the magnitude of the 'Thigh' data for 3 s windows was selected as the only feature to train the classifier, based on the accuracy values as mentioned in section 'Classification of static and dynamic activities'.

Classifier 1 was trained and evaluated with all 15 datasets across the 5 participants with 5-fold cross validation and the accuracy was 100%. Classifier 1 was further evaluated with a leave-one-subject-out approach. For each left-out participant, 3 days of data were used for testing, and roughly 90 seconds of data were taken from 4 static postures (4 postures $\times$ 90 s $\times$ 50 Hz $\times$ 3 days $=$ 54000) and 2 dynamic activities (2 activities $\times$ 90 s $\times$ 50 Hz $\times$ 3 days $=$ 27000) to evaluate the classifier.

Classification of postures. The inclination angles for the waist, thigh, and ankle for each posture from all 15 datasets are shown in Fig. 4. Figure 5 shows the same data in a 3D representation, with the waist, thigh, and ankle inclination angles on the three axes. The plots show four clusters corresponding to the four postures.

Classifier 2 had a 100% classification accuracy for both 5-fold cross validation and leave-one-subject-out methods. The given confusion matrix in Table 1 was based on a 5-fold cross validation method.

All the analyses presented above were conducted with the 'Right' leg data. The same analyses were conducted with the left leg to examine if there were any differences. Similar accuracies were observed from both Classifiers 1 and 2.

Analysis of "usual activities". By combining both classifier outputs the data were categorised into five categories, the four static postures plus dynamic movements as a fifth category. Again we observed that the accuracy remained the same at 100% even after combining both classifiers with the given dataset.

The data collected from the participants' "usual activities" for the rest of the day (i.e. non-ground truthed activities) were analysed to characterise the postural variations of the participants. Figure 6 shows one of the summary reports ('Participant A'). Each day, 'Participant A' was wearing the sensors for more than 8 hours during daytime hours. Three of the days were weekdays when 'Participant A' was mainly working (in front of a

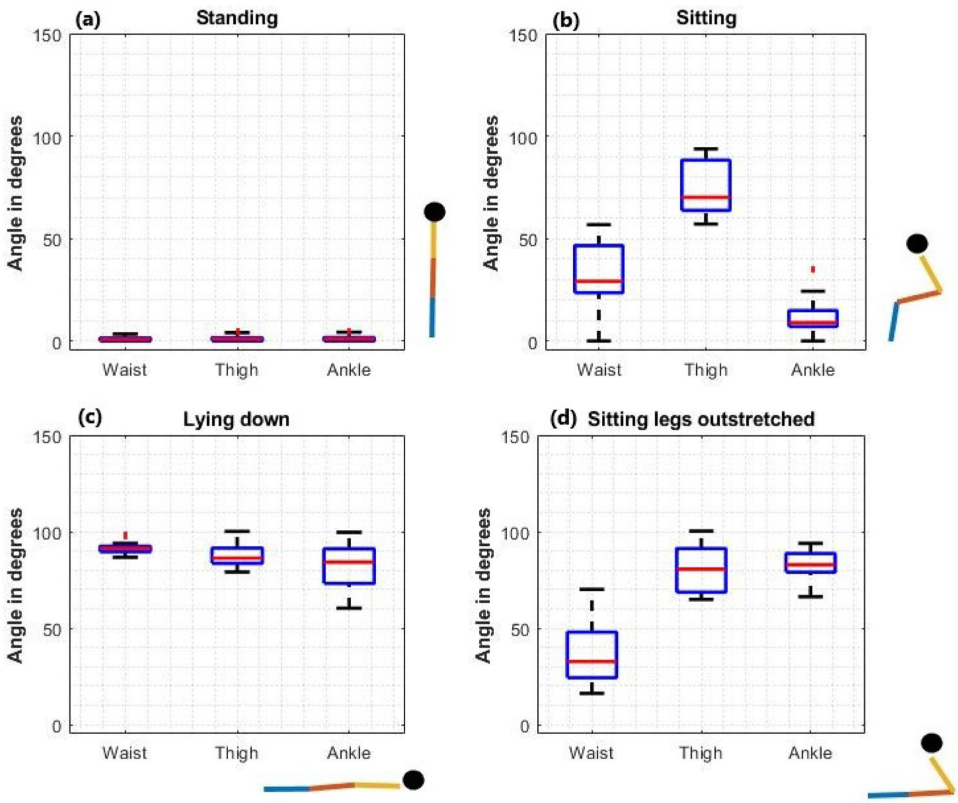

Figure 4. Inclination angles for the waist, thigh, and ankle from all 15 datasets for (**a**) standing, (**b**) sitting, (**c**) lying down, and (**d**) sitting with legs outstretched. The stick figures are drawn using the median value of the inclination angles.

computer) and during the weekend-day, the participant was doing miscellaneous activities including shopping, according to the diary reports.

By comparing the weekday plots against the weekend plot (Fig. 6a,b.1,c and d), the sensor data capture that 'Participant A' had been sitting and sitting with legs outstretched between 73% and 86% of the time throughout the data collection on weekdays. In contrast, on the weekend, the proportion of time spent sitting and sitting with legs outstretched was comparatively lower (35%). Moreover, the sensors captured a higher proportion of time spent lying down (14%) on the weekend, which corresponded to the participant having a nap and lying down on a sofa, according to their diary data. Further, during the weekend, the participant's dynamic activities and standing durations made up a higher proportion of the activities (51%), compared to weekdays. During the weekdays the total dynamic and standing data were between 13% and 25%.

According to Fig. 6b.1, on Day 2, 'Participant A' had spent 45% of their day in a 'sitting with legs outstretched' posture and 41% of the time sitting. In order to check why 'Participant A' had been sitting with legs outstretched for a longer period than that of sitting, the data were analysed against the diary data. Figure 6b.2 shows the distribution of postures based on the classifier (b.1) as compared with the participant's diary data (b.2). According to Fig. 6, it would appear that 28% of activity recorded in the diary as 'sitting' was classified as 'sitting with legs-outstretched', and roughly 5% of dynamic movements from the diary data appear to be classified as 'standing' data.

In order to understand these discrepancies better, the classifier output and the diary data were plotted alongside the corresponding angle data of the waist, thigh and ankle and the z-axis of acceleration from each sensor (Fig. 7).

Figure 7a shows a data segment where the classifier alternates between 'sitting' and 'sitting with legs outstretched' even though, that entire segment was recorded as 'sitting' in the diary. Within that segment, the ankle angles changed between 30° and 60°, resulting in the classifier distinguishing them as 'sitting' and 'sitting with legs outstretched'. When 'Participant A' was asked about the data, they stated that during some segments their legs were in different positions and they might have stretched their legs while working. By considering all these factors it could be said that unconsciously the participant might have stretched out the ankles from the proper sitting posture without changing the waist or thigh, which could be the reason for the discrepancies in 'sitting ' vs 'sitting with legs outstretched' data between the classifier output and the diary data.

Similarly, Fig. 7b shows an instance where there was a discrepancy in standing and dynamic activities in classifier output versus diary data. The participant recorded a period of fidgeting (from 13:40) which was annotated as dynamic activity. Examination of the sensor data, however, indicated that the data also included periods of standing which were not noted in the diary, yet were classified by the classifier as standing. Figure 7b shows

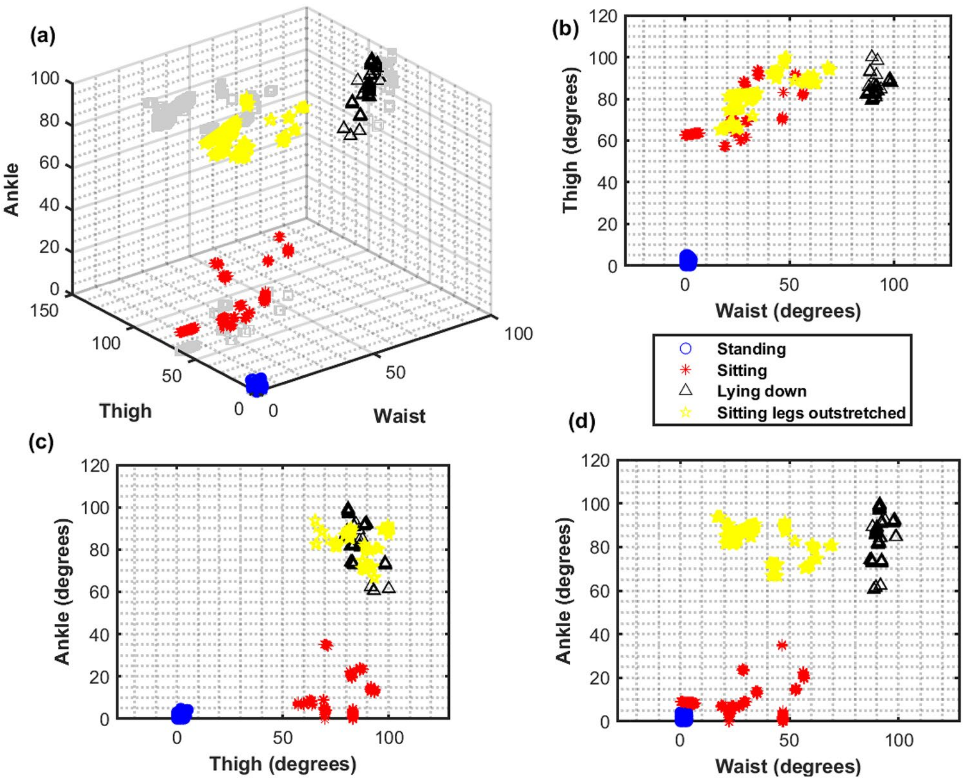

Figure 5. (**a**) 3D plot of the inclination angles. Shadows of the data are projected in grey onto the walls of the graph. Four clusters correspond to standing (blue 'o'), sitting (red 'x'), lying down (black '△') and sitting with legs outstretched (yellow pentagon). Projections of the data are shown in (**b**) 'thigh' vs 'waist', (**c**) 'ankle' vs 'thigh' and (**d**) 'ankle' vs 'waist'.

True class	Posture 1	65785	0	0	0
	Posture 2	0	69015	0	0
	Posture 3	0	0	67175	0
	Posture 4	0	0	0	58605
		Posture 1	Posture 2	Posture 3	Posture 4
		Predicted class			

Table 1. Confusion matrix for Classifier 2 (posture classification) Posture 1: Standing, Posture 2: Sitting,Posture 3: Lying down, Posture 4: Legs outstretched. There were approximately 22.5 minutes (67,500 samples) of data per activity (maximum of 90 seconds per posture per day x 15 participant-days).

one such fidgeting segment from the whole dataset. Not only by considering the classifier output, but also by examining the flat lines of the waist, thigh and ankle accelerometer signals, it can be said that there were static (standing) segments within that fidgeting segment.

This paper focused on analysis of static postures based on accelerometry. Further, this paper gives an insight as to how the different window sizes can be used in feature vectors in training classifiers under different scenarios. Both classifiers implemented in this study had 100% accuracy when trained and evaluated with an annotated dataset. This dataset was highly-selected and accuracies could decline with more naturalistic activities that include, for example, sitting with the legs crossed. Nevertheless, the results indicate that sensors embedded in loose clothing are significant as a way of capturing posture information. Comparison of the diary data and the posture classifier output indicates that a significant percentage of activity during a person's days can be captured by postures that can be recognised with sensors only on the lower body (waist, thigh, ankle). Still, inclusion of upper body sensor data could be useful to understand whole body postures.

Even though this study is limited to the classification of data into four basic postures, further improvements are possible by using a different method for estimating the inclination angle. For instance, a rotation matrix approach as described in "Estimating sensor inclination angle with a rotation matrix" section could be used, which would allow estimation of angles from 0° to 360° (versus the arccos method which estimates angles

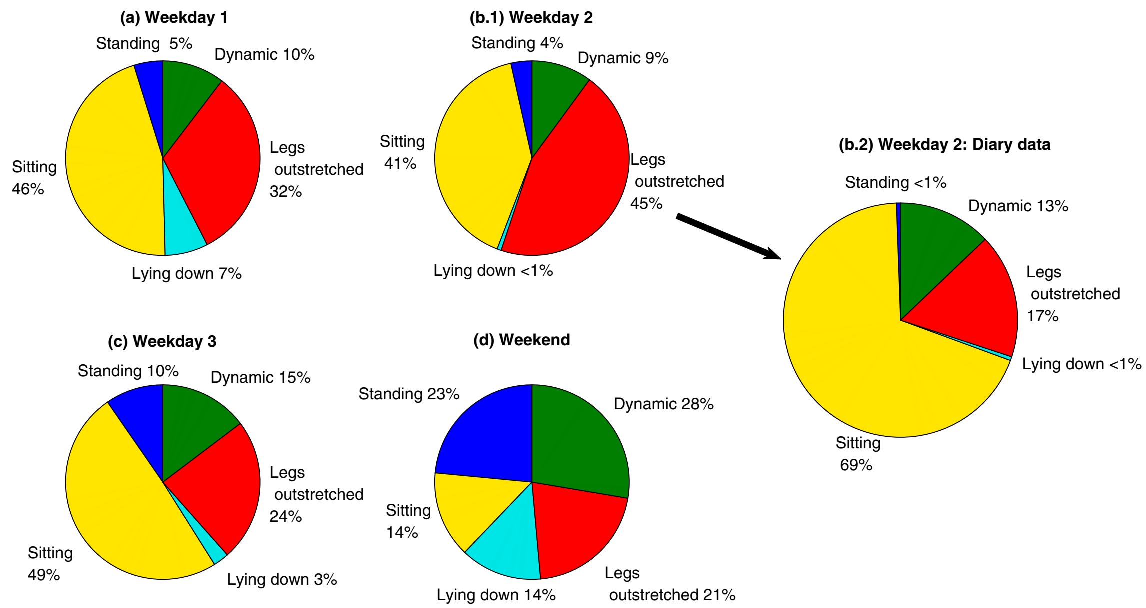

Figure 6. Four days' activity summary report for 'Participant A', based on analysis of the sensor data (**a**, **b.1**, **c** and **d**) and activity percentages based on diary data for Weekday 2 (**b.2**). This includes three weekdays and one weekend day. Compared to weekdays, there was more standing and dynamic movements at the weekend. Also, the participant was sitting most of time during the weekdays with less time spent in dynamic movements.

between 0° and 180°). With some adjustments to the method of estimating the inclination angles to be able to distinguish, for example, between "forward" and "backward" inclinations, there is a possibility of using these clothing-mounted wearable sensors in analysing 'sleeping' postures such as "supine position", "prone position", "right position", "left position", and "sitting position" as mentioned in[30].

We acknowledge that this study was conducted with a limited number of participants, nevertheless the data collection with each of the 5 participants was extensive (1–4 full days each, resulting in more than 90 hours of data) and systematic. Altogether, 15 datasets (i.e. 15 participant-days) were used to train and evaluate the classifiers, and we believe that this analysis is sufficiently robust to show that the clothing-mounted sensor data can be used productively in posture analysis.

Dynamic activity classification is as important as posture classification, and is an important direction for future work. One of the main benefits of looking at dynamic activities is the possibility of analysing the intensity of physical activities. Physical inactivity causes many health issues[31] and classification of dynamic activities could help provide insights that are relevant in healthcare monitoring. Another area for further work is to extend this study to analyse the upper body data, to improve the static posture and dynamic movement classifications.

Conclusion

Monitoring posture and classifying activities for long-term healthcare can be challenging. In order to achieve a reasonable level of accuracy, more sensors can help but can be difficult or cumbersome for the person to wear. A solution is to mount the sensors into everyday clothing, so the data collection is unobtrusive for the individual. This study analysed data from 3 sensors mounted along the lateral seam of both legs of loose-fitting trousers, corresponding to the waist, thigh, and ankle. Three features (inclination angles of the waist, thigh, and ankle) were used to implement a posture classifier, which achieved 100% accuracy. Hence, we conclude that sensors mounted on loose clothing can be used successfully for posture classification.

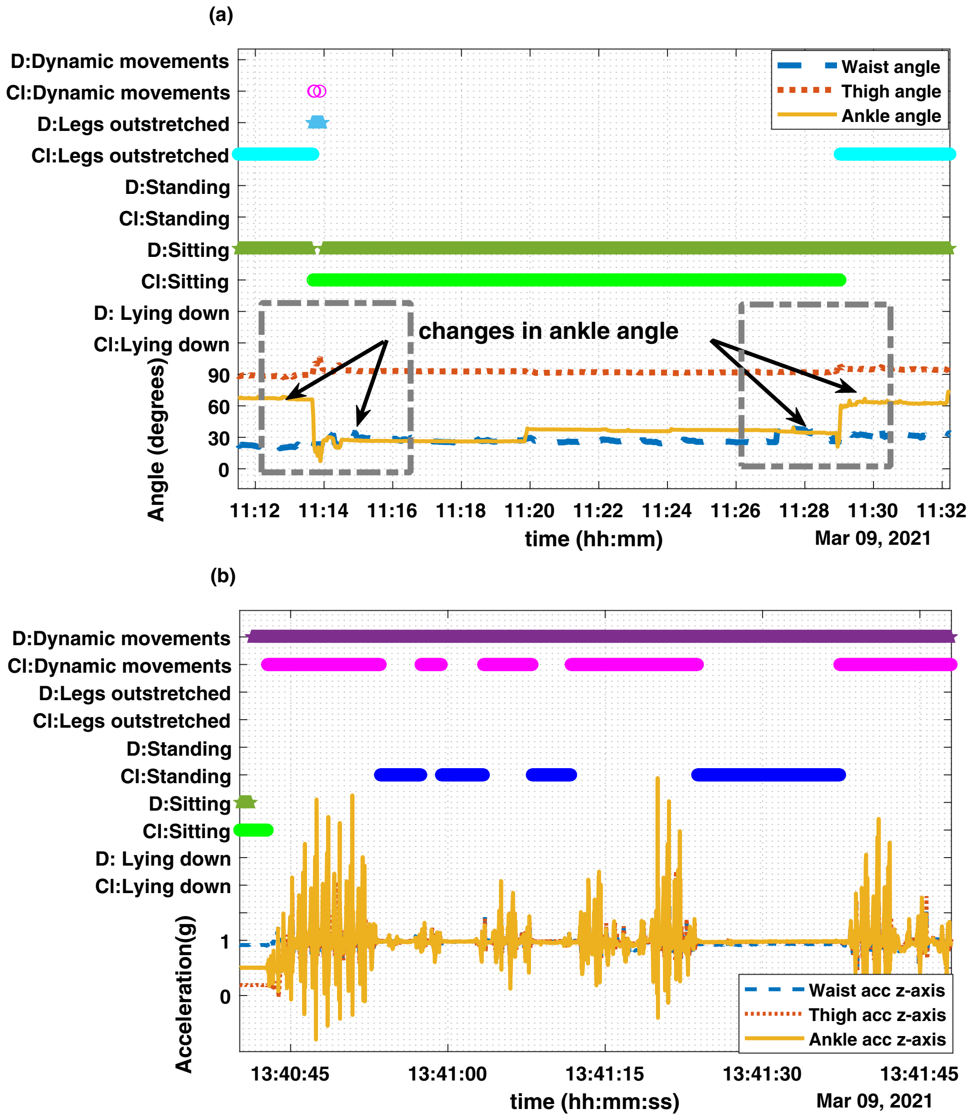

Figure 7. Two segments from Participant A's Day 2 data with classifier output and diary data. Plot (**a**) shows the sensor to vertical angles of the waist (blue dash), thigh (red dot) and ankle (solid yellow) for a period of 'sitting' as per the diary record. The classifier output (Cl) and diary data (D) are shown in the upper part of the graph. The participant has only changed the ankle angle while the waist and thigh remain the same, resulting in the classifier output changing between 'sitting' and 'sitting legs outstretched'. Plot (**b**) shows a period of fidgeting as per the diary data. The z-axis of the accelerometers on the waist (blue dash), thigh (red dot) and ankle (solid yellow) are shown. The classifier classified some segments as standing (shown in blue), while the diary recorded the whole segment as fidgeting (dynamic).

Data availability
All data analysed in this paper are included in this article (and its supplementary information files).

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Author contributions
Conceptualisation, methodology, and analysis, U.J., F.H. and W.S.H; resources, B.J.; investigation and visualisation, U.J.; writing—-original draft preparation, U.J.; writing—-review and editing, ALL; All authors read and approved the final manuscript.

Competing interests
The authors declare no competing interests.

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Chapter 6

Comparing Loose Clothing-mounted Sensors With Body-mounted Sensors in the Analysis of Walking

Chapter 3 concluded that the clothing-mounted data highly correlate with body-mounted sensor data during static postures than during the dynamic activities. However, the sensors used in that comparison were a bit heavy (19 g). Hence, there was a need to analyse how the lightweight body-mounted sensor data correlate with lightweight clothing-mounted data with respect to dynamic activities.

This chapter covers the fourth aim of the research, i.e. collecting a supplementary dataset covering the lower body with 6-9 lightweight sensors mounted on body and clothing to quantify the correlation between the sensor pairs with respect to 'walking' data.

Data were collected from three healthy participants and each participant wore the same clothing with sensors for 2 days. The correlation coefficient values were compared with respect to inclination angles of each sensor pair. The inclination angles were calculated based on quaternions using the Madgwick MARG algorithm [1].

Quaternion representation of orientation

The following is a brief discussion about quaternions and their use as a compact representation of rotation transformations. Quaternions can be considered as an extension of complex numbers and were first described by sir William Hamilton[2]. in 1843.

Quaternions are often identified as a quadruple of 4 real numbers $q = (q_0, q_1, q_2, q_3)$ with an arithmetic that extends the concept of a complex number but with three complex variables i, j, k. The rules for quaternion arithmetical operations such as addition, multiplication, conjugation and inverse are well defined and can be easily programmed.

One useful notation of a quaternion quadruple is to present the 4 elements of the quaternion as a scalar and a 3 element vector, so that $q = (q_0, q_1, q_2, q_3) = (q_0, \vec{q_v})$, and $\vec{q_v} = (q_1, q_2, q_3)$. This notation allows us to consider spatial 3 element vectors as a subspace quaternions where $q_0 = 0$.

Two important arithmetic operations are needed when using quaternions to represent a rotation, multiplication and the conjugation of a unit quaternion.

The multiplication of two quaternions q and r when in their "scalar plus vector" form is then given by the following notation where $(\cdot) \times (\cdot)$ is the vector cross product.

[1]https://x-io.co.uk/open-source-imu-and-ahrs-algorithms/
[2]https://www.maths.tcd.ie/pub/HistMath/People/Hamilton/

$$
\begin{aligned}
q \otimes r =& (q_0, \vec{q_v}) \otimes (r_0, \vec{r_v}) \\
=& (q_0 r_0 - \vec{q_v}.\vec{r_v}, \quad q_0 \vec{r_v} + r_0 \vec{q_v} + \vec{q_v} \times \vec{r_v})
\end{aligned}
$$

The conjugate of a quaternion $q = (q_0, \vec{q_v})$ requires simply changing the sign of the vector component, i.e.

$$q^* = (q_0, -\vec{q_v}) \tag{6.1}$$

A unit quaternion is usefully represented as

$$q = (\cos\left(\frac{\theta}{2}\right), \vec{u}\sin\left(\frac{\theta}{2}\right))$$

Where $\vec{u}$ is a unit vector and θ is any angle, however, this will later represent the angle of rotation or transformation of any vector about the unit vector $\vec{u}$ by an angle θ.

A unit quaternion has a magnitude of 1, and the magnitude of a quaternion is the square root of the sum of the squared elements, expressed with the notation used here is then $|q| = \sqrt{q_0^2 + \vec{q_v} \cdot \vec{q_v}}$ and now (for completeness) the quaternion inverse can then be constructed as

$$q^{-1} = \frac{q^*}{|q|}$$

With these tools it is then possible to use the unit quaternion identified in equation 6.1 to compute the coordinate transformation of a vector $\vec{r}$ expressed in a sensor frame $\{S\}$ (notated as ${}^{S}\vec{r}$) to a world frame $\{\mathrm{NWU(North, west, up)}\}$ (notated as ${}^{\mathrm{NWU}}\vec{r}$). That is

$${}^{\mathrm{NWU}}\vec{r} = q \otimes {}^{S}\vec{r} \otimes q^* \tag{6.2}$$

More correctly this transform can be expressed as

$$^{\mathrm{NWU}}\vec{r} = q \otimes {}^{S}\vec{r} \otimes q^{-1}$$

However, if q can be assured as a unit quaternion, it can be reverted to use it in the conjugate form as given in equation 6.2.

Methodology, data analysis, discussion and conclusions are explained in detail on the attached paper titled "Comparing Loose Clothing-mounted Sensors With Body-mounted Sensors in the Analysis of Walking".

Further analyses carried out with all the participants are listed as Appendix C.1 and C.2.

From this analysis, it was noted that the clothing data were able to represent gait related information in a productive way.

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Article

Comparing Loose Clothing-Mounted Sensors with Body-Mounted Sensors in the Analysis of Walking

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Abstract: A person's walking pattern can reveal important information about their health. Mounting multiple sensors onto loose clothing potentially offers a comfortable way of collecting data about walking and other human movement. This research investigates how well the data from three sensors mounted on the lateral side of clothing (on a pair of trousers near the waist, upper thigh and lower shank) correlate with the data from sensors mounted on the frontal side of the body. Data collected from three participants (two male, one female) for two days were analysed. Gait cycles were extracted based on features in the lower-shank accelerometry and analysed in terms of sensor-to-vertical angles (SVA). The correlations in SVA between the clothing- and body-mounted sensor pairs were analysed. Correlation coefficients above 0.76 were found for the waist sensor pairs, while the thigh and lower-shank sensor pairs had correlations above 0.90. The cyclical nature of gait cycles was evident in the clothing data, and it was possible to distinguish the stance and swing phases of walking based on features in the clothing data. Furthermore, simultaneously recording data from the waist, thigh, and shank was helpful in capturing the movement of the whole leg.

Keywords: accelerometer; body-mounted sensors; clothing-mounted sensors; gait cycle; healthcare; human movement; IMU; sensor to vertical angle; wearable devices

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1. Introduction

Gait analysis can give a good indication about one's health, as walking is a common physical activity for many people, performed everyday, and it highly depends on the central nervous system [1,2]. Hence, if there is any functional disorder in the central nervous system, it is reflected in gait patterns [3]. The way gait could be affected by nervous system disorders can be seen with dementia patients and people with Parkinson's [4,5]. Furthermore, even healthy older adults with slow gait speed may experience deterioration in cognitive function [4]. Hence, monitoring gait patterns could be a method for the early diagnosis of musculoskeletal and central nervous system disorders [3].

Gait analysis technologies can broadly be divided into two categories, non-wearable sensor and wearable sensor technologies [6]. Usually, non-wearable technologies, such as camera-based systems and ground reaction force sensors (GRF), are used in laboratory settings, whereas wearable sensor technologies, such as accelerometers, gyroscopic sensors, magnetometers, force sensors, extensometers, goniometers, active markers, electromyography, sensing fabrics and smartphones, can be used outside and inside the laboratory setting [6]. However, due to having features such as usability, portability, low cost, low power consumption, high sensitivity and small sizes, wearable sensors are commonly used in gait and other movement analyses research [1,6]. In gait research, wearable sensors have been mounted on feet/shoes [7–11], knees, thighs [12], ankles [5,13], shanks [14–16], chests [13] and waists [13,17] to analyse the gait parameters such as stride velocity, stride length, step length, cadence, step width, step angle, step time, swing time, stance time, gait phase, joint angles and momentum [6].

In many research studies, gait parameters are extracted from multiple places, such as the hip, knee and ankle joints, and researchers investigate combining the data collected from the different sites [18] Furthermore, other studies have stated how results could be enhanced by using multiple sensors in gait analysis and gait classification [19,20]. Gao et al. have identified the benefits of using multiple sensors with light-weight algorithms as compared with using single wearable sensors with computationally demanding processing to train complex classifiers [21].

However, wearing multiple sensors on a long-term basis could be a cumbersome task for the wearer. Moreover, if the sensors are not reliably worn in the same place in the same orientation every time, the data would not be consistent, which makes the data analysis process more complex. Clothing-mounted sensors and smart garments could potentially address these issues. An important step toward the use of clothing-mounted sensors for gait analysis and/or long-term monitoring, however, is to verify the reliability of the data, for example, by validating the data from clothing-mounted sensors against those from body-mounted sensors. There are only a limited number of research studies on this topic. One such study validated the association between readings from sensors mounted in tight-fitting clothing and sensors mounted on the body with respect to a single activity (dead-lifting) [22]. Another work showed that sensors attached onto fabric produced better signal variations compared with sensors attached with accessories (e.g., bands) that could be used in activity classification [23]. There are research studies conducted with loose clothing-mounted sensors in investigating movement and fall detection [24–26]. However, it was noted that these clothing data have not been validated/compared with body-mounted sensor data with different activities. As such, there is a need for a systematic analysis to assess the extent to which everyday wear clothing-mounted sensor data can be used in movement analysis and activity classification.

In our previous work [27] conducted with Actigraph (https://actigraphcorp.com, accessed on 15 November 2019) sensors, the correlations between clothing- and body-mounted sensors in dynamic activities were found to be lower than the correlations observed during static activities such as standing and sitting, due to the sensors being a bit heavy (19 g). Hence, the present study investigates the use of light-weight sensors in the clothing, specifically comparing how well the data from clothing correlate with data from sensors mounted on the frontal side of the lower body in gait analysis. In contrast with studies involving tight garments [13,28], in this study, we investigated everyday loose clothing, as this is likely to be more comfortable and acceptable for wearers.

2. Background

A gait cycle consists of two main phases (stance and swing phases), and they are further categorised into eight sub-phases [11,29,30]. Stance phase makes up approximately 60% of a gait cycle, and it starts from initial contact (IC)/heel strike (HS), followed by loading response (foot flat), mid-stance, terminal stance and toe-off (TO) [11,29,30]. The remaining 40% of the gait cycle consists of the initial swing, mid-swing (MS) and terminal swing.

A complete gait cycle is considered to be from one IC/HS to the next IC/HS with the same foot [11,29–32]. A number of studies have used gyroscope data to track 'HS' and 'TO' in gait cycles from foot/shoe-mounted sensors [8,9,16,29,33] while others have used either accelerometry alone or both gyroscope and accelerometer data combined. With accelerometer data, MS [12], HS [10] and terminal contact (foot-off) [14] can be used to track gait cycles. When using both accelerometer and gyroscope data, HS, TO, MS and terminal stance can be used to track gait cycles [5,7].

The present study focuses on examining sensor-to-vertical angles as a measure of the sensor's orientation in space relative to vertical. As a first step, the orientation of each sensor had to be calculated. There are many ways of estimating the orientation of inertial measurement units (IMUs) and magnetic, angular rate, and gravity (MARG) sensors. While an IMU (combination of an accelerometer and a gyroscope) can estimate attitude with respect to the direction of gravity, MARG sensors can estimate orientation considering both the direction of gravity and the magnetic field of the earth [34]. Further, as IMU data are susceptible to noise, sensor fusion techniques have been proposed as a reliable way to estimate orientation [35]. Three possible ways to represent orientation are Euler angles, quaternions and direction cosine matrices (DCM) [35]. In this study, we express sensor orientation as quaternions. Commonly used algorithms that estimate orientation with quaternions as outputs are described by Mahony et al. [36], Madgwick et al. [37] and Sabatini [38]. For this study, the algorithm implemented by Madgwick et al. was used to estimate the orientation quaternions.

Regarding data collection methodologies, many of the above-mentioned gait analysis studies used body-mounted wearable sensors. There were a smaller number of studies using clothing mounted sensors in gait analysis; however, the results were promising [13,39,40]. Cleland et al. [13]. used a harness around the chest and waist with three sensors to compare step counting from body- and clothing-worn sensors Niazmand et al. [39] studied accelerometers mounted in ordinary trousers to identify freezing of gait in people with Parkinson's, and their algorithm outputs were compared with a physician's report. They reported an 88.3% sensitivity. Cha et al. [40] investigated the use of piezoelectric sensors mounted in loose trousers to recognise walking/periodic motion and concluded that it was possible to detect walking segments from the data at 93% accuracy compared to an algorithm developed by Cha et al. [41].

The present study aims to investigate how well the data from body-mounted sensors correlate with that from clothing-mounted sensors in terms of their orientation angles during walking and also what information can be extracted from multiple clothing-mounted sensors on trousers. de Jong et al. [15] studied sensors placed on the frontal and lateral sides of the upper shank during walking in terms of the shank-to-vertical angle, which is a parameter commonly used to describe orthosis alignment. Our study also involves sensors placed on the frontal (body) and lateral (clothing) sides, and we compare waist and thigh sensor pairs in addition to shank sensor pairs. Further, as in Lee et al.'s analysis, which presented visualisations of gait characteristics based on multiple joint angle information [18], we present the gait information in 3D plots incorporating information from multiple parts of the body, as well as using phase portraits.

3. Materials and Methodology

3.1. Materials

Our sensing system consisted of between 6 and 9 IMUs (based on the Bosch Sensortec BMI160 smart IMU) all using a synchronous bus and connected via flat ribbon cable to form a "sensor string". Our in-house PCB design was fabricated by a commercial company at a cost of approximately 10 GBP per sensor. The bespoke sensors were approximately $15 \times 12 \times 7$ mm each and had a combined weight of less than 14 g, and the inter-connecting cables weighed approximately 110 g. This sensor string was connected to a battery-powered Raspberry Pi, where the data were stored. The Pi and battery were worn in a waist pouch attached using a belt (Figure 1). Data were sampled at 50 Hz. The range of the accelerometers was ± 16 g with a 12-bit resolution. The BMI160 IMU includes gyroscope, accelerometer and magnetometer readings.

Two sets of IMUs were worn by participants. One set was mounted inside the clothing, with three sensors along the lateral side of the lower body (waist, upper thigh and lower-shank) on the right side. The second set of IMUs was taped to the skin on the frontal side of the body at comparable positions to those of the sensors in the clothing, also on the right side (Figure 1). To attach the sensors to the clothing, the sensors were taped securely along the seams of the clothing in the chosen position, and cotton bias binding was taped on top of the sensor string using double-sided tape for fabric. In this way, the sensors were not outwardly visible and were also not in contact with the skin of the wearer. The body-mounted sensors were also part of the 'sensor string', and those sensors were encased in small woven pouches and taped to the skin/ body using microporous surgical tape to minimise the movements of the sensors.

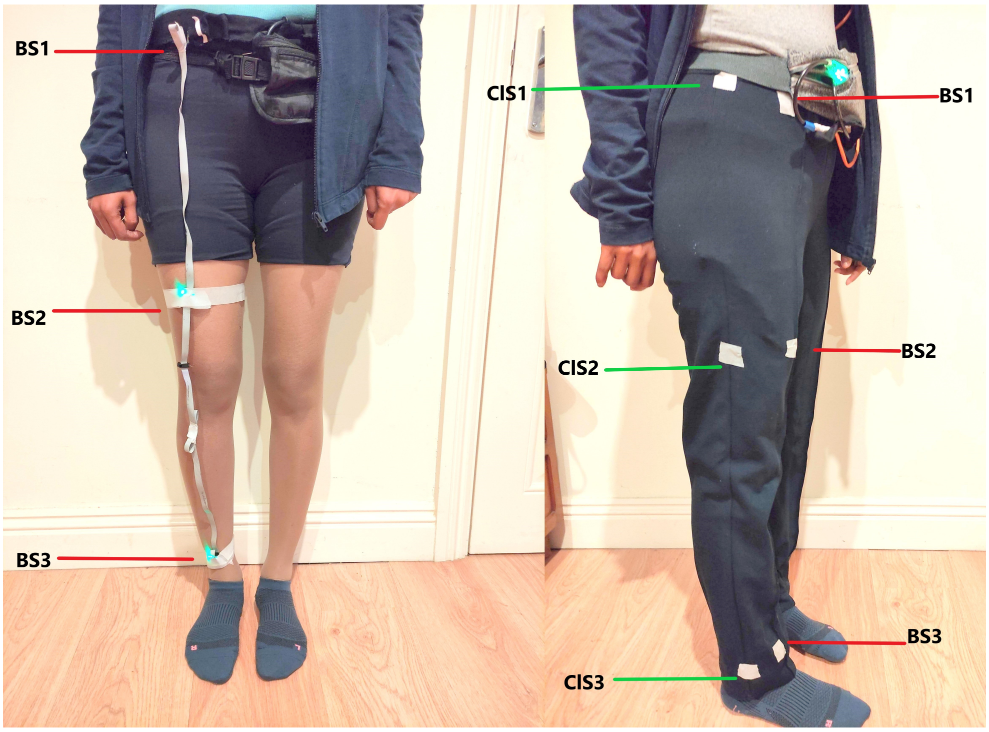

Figure 1. Sensor placement. On the body, there were three sensors on the frontal side of the body (BS1—waist, BS2—thigh, and BS3—lower-shank). On the clothing, there were three sensors along the lateral side of the lower body (ClS1—waist, ClS2—thigh and ClS3—lower-shank) in comparable positions to those on the body. Tape is used here to show the positions of the body-mounted and clothing-mounted sensors; however, in practice, neither was visible from the outside.

3.2. Data Collection Procedure

Three healthy participants (age range: 35–36 years old; 2 males and 1 female) took part in this study. Each participant provided a pair of their own trousers in their usual size, and the researcher attached the sensors to the clothing. The male participants chose cotton-blend fleece jogging trousers, and the female participant chose loose cotton slacks. Even though both male participants wore jogging trousers, they were not of the same type. One participant's trousers were baggy at the thigh, compared to the other participant's. After placing/fixing the body-mounted sensor string, the participants were asked to put on the trousers with sensors and to connect the strings together to start the data collection.

Each day, the participants were asked to perform a set of predefined activities that included walking, with each activity contributing about 2 minutes' data. The activities were: (1) standing still, (2) sitting on a chair, (3) 5 sit-to-stand and stand-to-sit cycles, (4) 5 leg raises, and (5) walking back and forth. These activities were video recorded to serve as a ground truth. Even though this analysis focuses only on walking data, 'standing', 'sit-to stand' and 'leg raising' data were also used for the sensor alignment as described in Section 3.3.1.

The study was reviewed by the research ethics committee of the School of Biological Sciences, University of Reading, UK and given a favourable ethical opinion for conduct (reference SBS 19- 20 31).

3.3. Data Analysis

We analysed the data from the walking activity from three participants over two days each. The data were first pre-processed (Section 3.3.1) and then segmented into individual gait cycles (Section 3.3.3). For each gait cycle, the sensor-to-vertical angles were estimated (Section 3.3.2) and used as the basis for comparing clothing-mounted with body-mounted sensors (Section 3.3.4).

3.3.1. Pre-Processing

The data were collected in a compressed format on the Raspberry Pi and were transferred to a PC, decompressed and analysed in MATLAB.

As the initial orientations of the sensors relative to the limbs and to the world were not known, two rotation matrices were applied to each sensor dataset to transform the data into a common coordinate frame. A first rotation matrix was applied to align the z-axis of the sensor data with the direction of gravity. This rotation was derived from standing data, assuming that while the participant was 'standing upright', the limbs were all vertical and the only accelerations measured by the sensors were the accelerations due to gravity. The rotation was computed using Rodrigues' rotation formula [42] by identifying the axis for rotation as being perpendicular to both the gravity vector and the z-axis.

A second rotation was applied to align the x-axis with the anterior-posterior direction in the sagittal plane and the y-axis with the medial-lateral direction perpendicular to the sagittal plane. The computation of the second rotation was based on finding the direction of forward-backward accelerations during movements that lie primarily within the sagittal plane, mentioned in Section 3.2 (e.g., sit-to stands, leg raising and walking). Figure 2 shows the alignment of the lower shank sensor. After this process, the clothing-mounted and body-mounted sensors can be assumed to be 'axis' aligned with the participant.

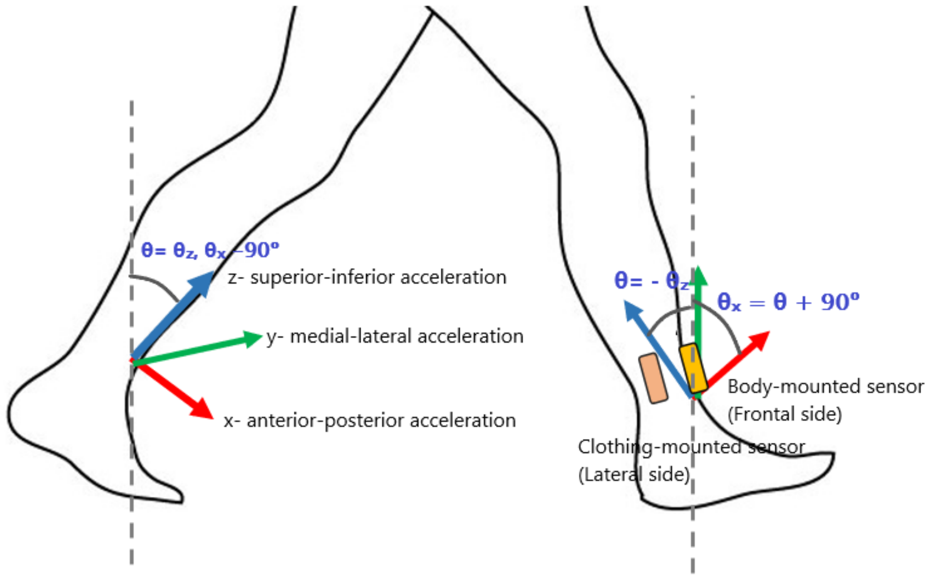

Figure 2. Location of sensors and corresponding coordinate frame $\{S\}$. Anterior-posterior accelerations of walking are measured in the sagittal plane and are principally measured by the x and z-axis in the sensor frame $\{S\}$. Angular velocities are principally measured by the y-axis of $\{S\}$. θ has a negative value when the leg is inclined (back leg, left) and a positive value when the leg is reclined (front leg, right).

The accelerometer and gyroscope data were low-pass filtered using a second-order Butterworth filter with a 3 Hz cut-off. The filter was run on the data both forwards and backwards to minimise phase distortions.

3.3.2. Sensor-To Vertical Angle Estimation

The primary accelerations of the leg and body segments during walking will be in or parallel to the sagittal plane with the rotational velocity vectors considered perpendicular to this plane. Following the pre-processing described in Section 3.3.1, it may be assumed that the sensor coordinate frame as shown in Figure 2 aligns so that the x and z-axis are contained in the sagittal plane. The y-axis is then aligned so as to measure the principal angular velocities of movement.

Inertial data from individual sensors placed on the clothing and attached to the skin was converted to quaternions using Madgwick's algorithm [37] (https://github.com/xioTechnologies/NGIMU-Software-Public, accessed on 21 September 2021). The algorithm returns an estimate q of the quaternion values that relate the sensor coordinate frame $\{S\}$ to a north (x-axis), west (y-axis), and up (z-axis) global frame $\{\text{NWU}\}$. These quaternions were assumed to be a reasonable estimate of the sensor frame $\{S\}$ orientations in this study.

Computing the sensor-to-vertical angle through the gait cycle is now possible by considering any vector in the sensor frame ${}^{S}\vec{r}$ and computing its coordinates in the ${}^{\text{NWU}}\vec{r}$ frame using

$$^{\text{NWU}}\vec{r} = q \otimes {}^{S}\vec{r} \otimes q^*$$

Thus the x-axis of the sensor frame (${}^{S}\vec{r} = \begin{bmatrix}1 & 0 & 0\end{bmatrix}^T$) and the z-axis (${}^{S}\vec{r} = \begin{bmatrix}0 & 0 & 1\end{bmatrix}^T$) have the respective coordinates

$$^{\text{NWU}}\vec{x} = \begin{bmatrix} q_0{}^2 + q_1{}^2 - q_2{}^2 - q_3{}^2 \\ 2q_1q_2 - 2q_0q_3 \\ 2q_0q_2 + 2q_1q_3 \end{bmatrix} \quad \text{and} \quad {}^{\text{NWU}}\vec{z} = \begin{bmatrix} 2q_1q_3 - 2q_0q_2 \\ 2q_0q_1 + 2q_2q_3 \\ q_0{}^2 - q_1{}^2 - q_2{}^2 + q_3{}^2 \end{bmatrix}$$

Since we are only interested in the sensor-to-vertical angle measurement, only the last row of these two vectors is relevant, as they are the cosine of the angle between the sensor x-axis or z-axis and up. The remaining terms are only relevant for estimating the absolute orientation of the sagittal plane with respect to north.

Thus, the angle between the sensor x-axis and up is θ_x, and the angle between the sensor z-axis and up is θ_z, where

$$\begin{aligned} \theta_x &= \arccos(2q_0q_2 + 2q_1q_3) \\ \theta_z &= \arccos(q_0{}^2 - q_1{}^2 - q_2{}^2 + q_3{}^2) \end{aligned}$$

It may seem logical to use the angle between the z-axis and up as the sensor-to-vertical angle; however, as this is an inverse cosine, it is not possible to determine if the limb is leaning forward or backwards with respect to up while walking. An alternative solution is to use the orientation of the x-axis with respect to up. During a normal gait cycle, this angle will oscillate around 90° during walking, so an offset is subtracted from this angle, and the eventual calculation is

$$\theta = \arccos(2q_0q_2 + 2q_1q_3) - 90^\circ \tag{1}$$

The estimate of the angular velocity is simply that of the gyroscope y-axis, which, due to the preliminary processing, is also the axis perpendicular to the sagittal plane.

3.3.3. Extraction of Gait Cycles

To segment the data into individual gait cycles, the MS points (right before the foot was at the terminal swing) were identified from the lower-shank accelerometry, following the method described in [11]. That is, for each of the datasets, the peaks above 2 g and 1.8 g within less than a 1 s window were identified from the acceleration magnitude from the clothing-mounted and body-mounted sensors, respectively. These peaks were logged as the MS points [11].

The duration of each individual gait cycle was then calculated as the time between two MS points. For each participant for each day, the mean durations for clothing and body sensors were calculated. The data were then segmented into individual gait cycles using the MS point as the start of each gait cycle, and setting the length equal to the mean duration in order that all gait cycles could have the same length (avoiding the need for normalisation). The data from the waist and thigh sensors, which were synchronised with the lower-shank sensors, could then be segmented into individual gait cycles using the same start and end points determined from the lower-shank sensor.

This process of gait cycle extraction was performed programmatically, and to check the accuracy of the algorithm, the start and end points of each gait cycle were identified from the video ground truth and checked against the points that had been programatically identified.

For each gait cycle, initial contact (IC) and toe off (TO) points were identified as the local minima in the lower-shank gyroscope data around the medial-lateral axis (y-axis), as used by Tjhai and O'Keefe [9].

3.3.4. Comparison of the Body-Mounted and Clothing-Mounted Sensor Angles

After verifying the normality of the data [43], the correlation (Pearson's correlation coefficient) between the sensor-to-vertical angles of the clothing- and body-mounted sensors [44] was calculated for each individual gait cycle. In total, 465 gait cycles were analysed from the 3 participants (i.e., 465 correlation coefficients). The mean correlation coefficient value was calculated for each participant.

The difference between the angles of each sensor pair (subtracting the body-mounted sensor angle from clothing-mounted angle) was also calculated for each participant for 2 min of standing and at two points in the gait cycle. During standing, the angle differences were expected to be minimal, as the orientation correction performed during pre-processing (Section 3.3.1) should ensure that the data from both sensors were aligned with vertical.

For walking, the angle differences were calculated at two different points. One value was calculated at the IC point extracted based on the lower-shank sensor, with the rationale that the difference between the two sensors could potentially be greatest at this point in the gait cycle. A second value was calculated at the point where the lower-shank sensor on the body was vertical during stance phase, with the rationale that the difference between the two sensors could potentially be smallest at this point in the gait cycle. The angle differences between the body-mounted and the clothing-mounted sensors was calculated for each gait cycle at these two points, and the mean and standard deviation across all gait cycles was calculated for each participant.

4. Results

4.1. Extracted Gait Cycles

Figure 3a–c shows the data from the clothing-mounted sensor on the lower-shank for two gait cycles of one particpant, along with the extracted initial contact (IC), toe-off (TO) and mid-swing (MS) points. The local minima for extracting the IC and TO points could be clearly identified in the gyroscope data from the clothing-mounted sensor (Figure 3a). Similarly, the local maxima for extracting the MS points could be clearly identified from the accelerometer data of the clothing-mounted sensor ((Figure 3b). The same points (IC, TO and MS) marked on the waist, thigh and lower-shank acceleration data are shown in Figure 3(c.i–c.iii). Approximate MS points were extracted by using the peak values marked on Figure 3b based on the magnitude of lower-shank/ankle accelerometer data. Comparing with the MS points that were identified manually from the video, the programmatic approach correctly identified the points from the clothing-mounted sensor data with 97.9% accuracy, and at an accuracy of 99.7% in the body-mounted sensor data. Inaccuracies seemed to have occurred in the clothing data when some 'turning' data were identified as MS points by the algorithm. The analysis presented in the following sections considers only the gait cycles with correctly identified MS points.

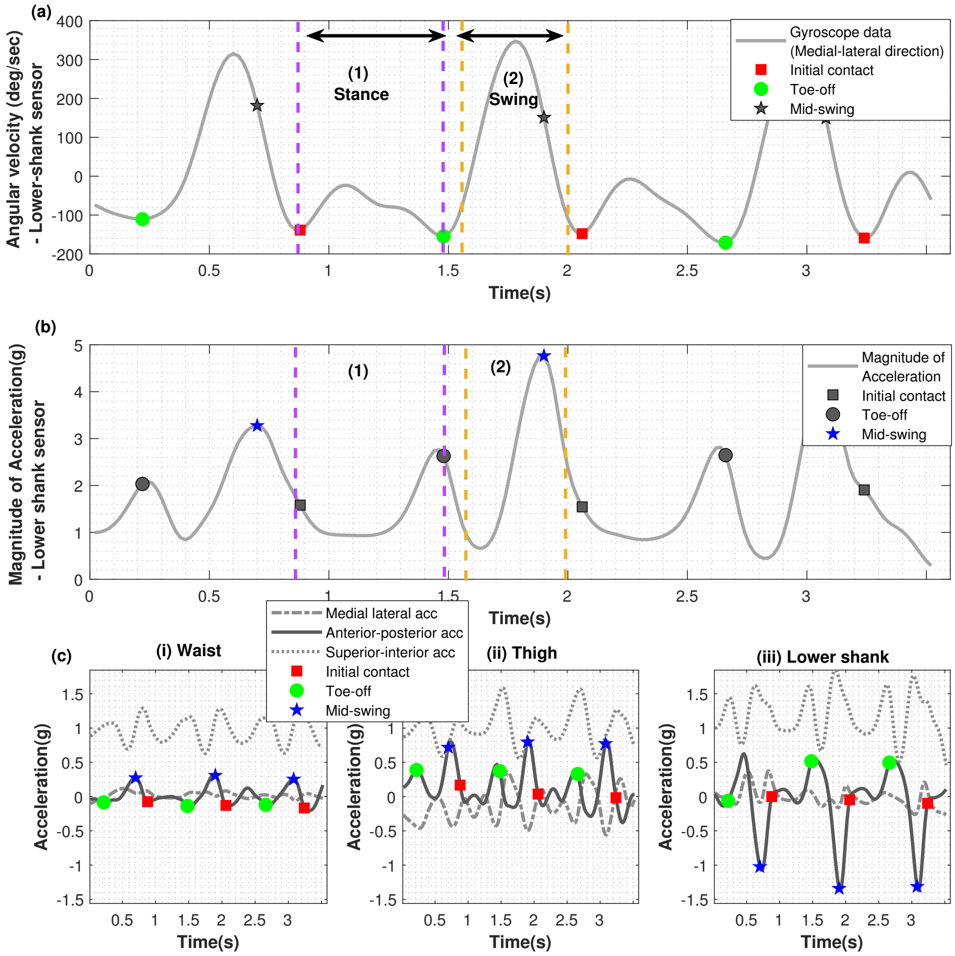

Figure 3. Data from the clothing-mounted sensors for participant 1, day 2. Initial contact and toe-off markers were extracted based on the gyroscope data (medial-lateral axis) from the lower shank (**a**), and the mid-swing markers were extracted based on the magnitude of the accelerometer data from the lower shank (**b**). In (**c**), the same timepoints are shown on the anterior-posterior accelerations for the i. waist, ii. thigh, and iii. lower shank. Segment (1) bounded by purple dashed lines indicates the 'stance' phase, and segment (2) bounded by yellow dashed lines indicates the 'swing' phase.

4.2. Sensor-to-Vertical Angles

The sensor-to-vertical angles for the body- (right side) and clothing-mounted (left and right sides) lower-shank sensors for Participant 2, day 1 are shown in Figure 4a. These lower-shank angles were comparable with the shank-to vertical angle analyses presented by Gujarathi and Bhole [30] and with the inverse angle values presented by de Jong et al. [15]. The signs for the present study are inverted to those of de Jong et al., as the authors used positive angles to represent when the leg was inclined and negative angles when the leg was reclined, while the convention was the other way around in the present study.

As described in Section 3.3.3, MS points extracted from the lower-shank acceleration data were used as the starting point to also segment the gait cycles from the waist and thigh sensors. In this study, 465 gait cycles were analysed across all participants. The mean for 67 gait cycles from one participant, for both body-mounted and clothing-mounted sensors, is shown in Figure 4b–d.

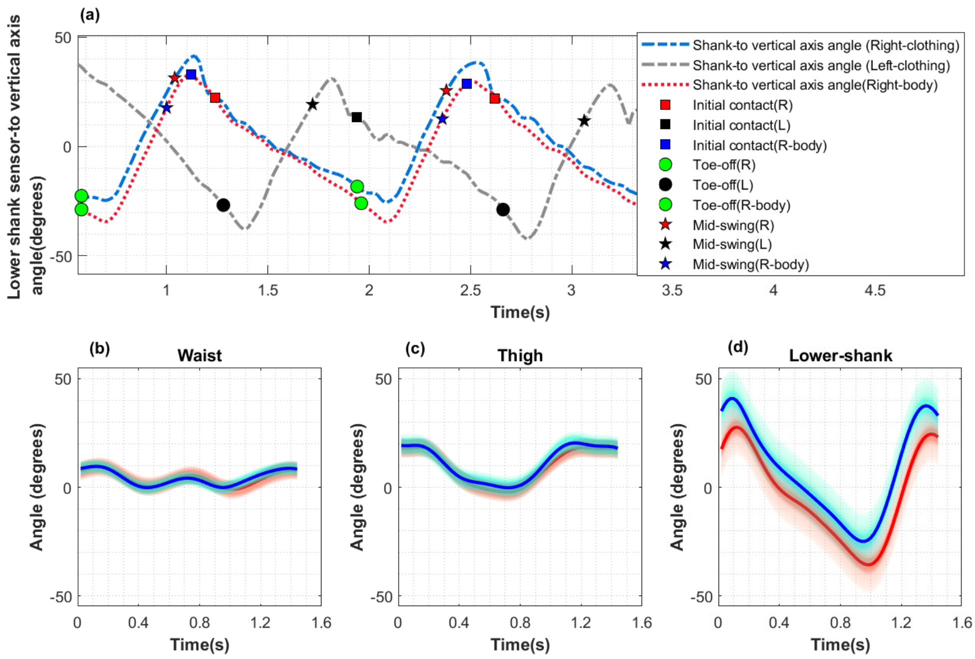

Figure 4. Body- vs. clothing-mounted sensor-to-vertical angle for Participant 2, day 2. (**a**) Exemplar initial contact (IC), toe-off (TO), and mid-swing (MS) markers on the lower-shank sensor data of the body (right leg) and clothing (left and right legs). (**b**–**d**) Mean gait cycles across 67 gait cycles for body-mounted (red) and clothing-mounted (blue) sensors for the (**b**) waist, (**c**) thigh, and (**d**) lower-shank sensors; shaded areas represent the standard deviation.

4.3. Waist, Thigh, and Lower-Shank Sensor-to-Vertical Angles

Figure 5 shows the sensor-to-vertical angles of the waist, thigh, and lower shank plotted against each other over the course of multiple gait cycles. Both the data for the body-mounted sensors (red) and for the clothing-mounted sensors (blue) are shown. Visual examination shows that both datasets follow a similar shape with a slight offset. The amount of offset may vary with clothing material. In this particular dataset, Participant 2 was wearing loose slacks, and hence, the lower-shank sensor might experience movement from the clothing in addition to the leg movement.

The mean angle differences between the clothing and body sensors are shown in Table 1. It can be noted that Participant 2's mean angle difference (row 2, column 9) at the IC stage was the highest compared to the other two participants.

Figure 6 illustrates how the angular velocity changes against the sensor-to vertical angle over a gait cycle for each sensor by using phase portraits. The figure shows a typical gait cycle which follows the shape of the mean gait cycle, as shown in Figure 4. Approximate MS, IC and TO points are marked on each plot for body-mounted and clothing-mounted sensors. This shows that the clothing-mounted sensor data experienced a wider range of angles in walking, while having a similar body-mounted gait cycle shape in the phase portrait. Further, it could be noted that the MS, IC and TO points identified from clothing and body mounted sensors were close to each other (pair-wise).

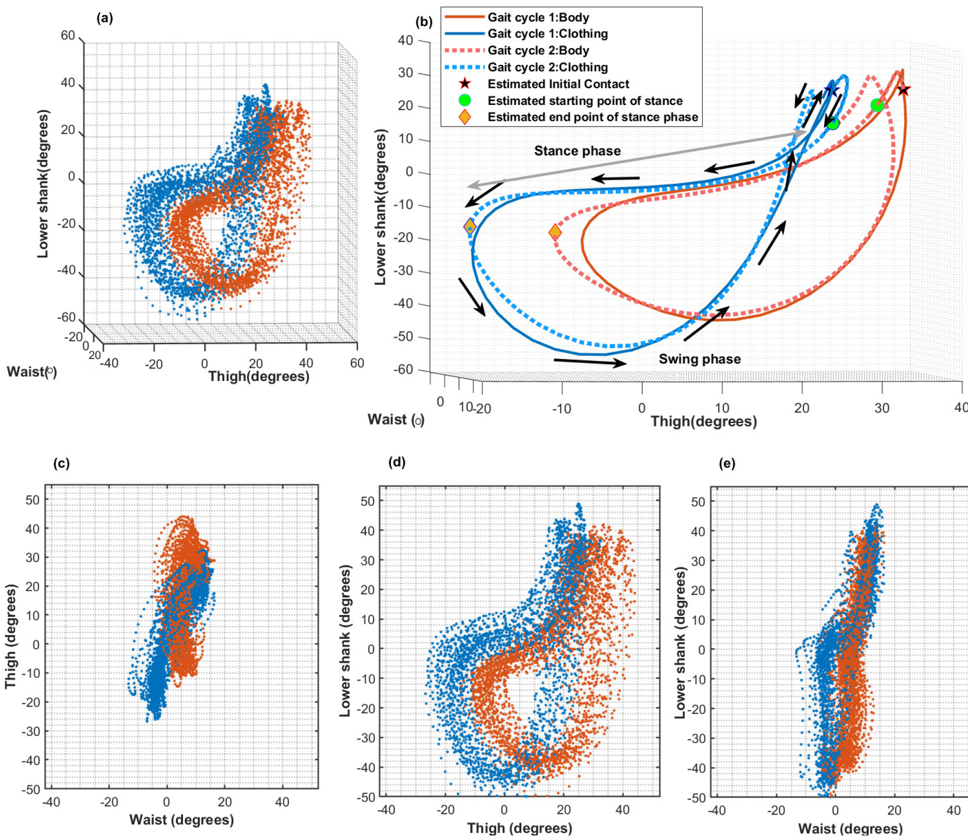

Figure 5. Sensor-to-vertical angles of the waist, thigh, and lower shank plotted against each other for 53 gait cycles from Participant 2, day 1. (**a**) The angles for body-mounted sensors (red dots) and clothing-mounted sensors (blue dots) plotted in a 3D space. (**b**) Two typical gait cycles from body-mounted (red) and clothing-mounted (blue) sensors. 'Green o' s are the approximate starting points of stance phases (Initial contact) and 'yellow diamonds' are the approximate end points of swing phases (toe off). The arrows show the direction of angle changes over the course of a gait cycle. (**c**–**e**) represent the angle data for 'thigh' vs. 'waist', 'lower shank' vs. 'thigh' and 'lower shank' vs. 'waist', respectively.

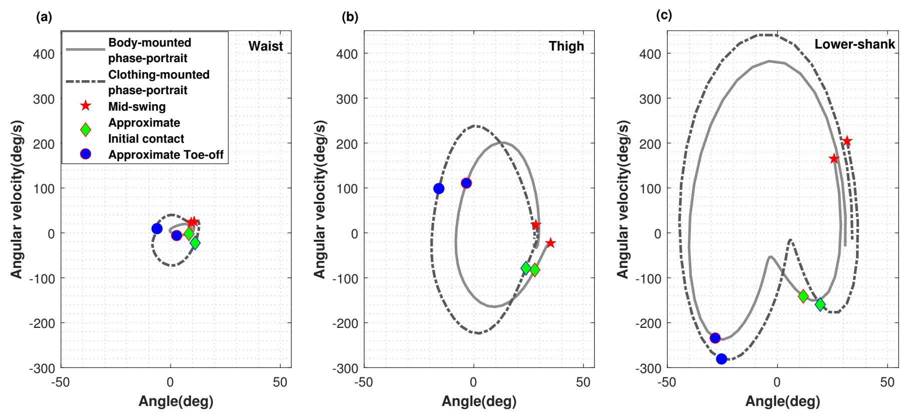

Figure 6. Phase portraits for a typical gait cycle from body-mounted and clothing-mounted sensor pairs from Participant 2, day 1. The angular velocity is plotted against the sensor-to-vertical angle for the (**a**) waist sensor pair, (**b**) thigh sensor pair and (**c**) lower-shank sensor pair. 'Red *'s denote the starting points (mid-swing, MS), 'green and cyan diamonds' denote approximate initial contact (IC) and 'blue o' s denote approximate toe-off (TO) for each cycle. These plots indicate that clothing-mounted sensors had a wider range of angle changes and angular velocity changes than the body-mounted sensors.

Table 1. Mean correlation coefficient (corr. coef.) between each sensor pair and mean angle differences (subtracting body-mounted sensor angle from clothing-mounted angle) with standard deviation values (denoted with ±). For standing, the angle differences were calculated over 2 min of data. For walking, the angle differences were calculated at initial contact (IC) and at the point when the lower-shank body-mounted sensor was approximately vertical. P3 did not have a waist sensor pair (indicated by '-').

	Clothing Type	Waist				Thigh				Lower Shank			
		Corr. Coef.	Standing	Walking IC	Walking Shank Vertical	Corr. Coef.	Standing	Walking IC	Walking Shank Vertical	Corr. Coef.	Standing	Walking IC	Walking Shank Vertical
P1	Jogging trousers	0.77	0.03° ± 0.52°	−1.95° ± 6.94°	2.11° ± 4.30°	0.93	0.06° ± 0.30°	−14.57° ± 8.47°	−8.82° ± 8.13°	0.97	0.14° ± 0.37°	2.12° ± 7.55°	2.83° ± 5.87°
P2	Loose slack	0.81	0.13° ± 0.34°	0.85° ± 2.45°	−1.60° ± 2.83°	0.96	0.01° ± 0.28°	−2.91° ± 7.60°	−4.00° ± 7.23°	0.98	0.03° ± 0.23°	11.16° ± 7.72°	7.20° ± 4.06°
P3	Jogging trousers	-	-	-	-	0.91	0.12° ± 0.30°	−6.27° ± 9.71°	−2.21° ± 3.62°	0.97	−0.07° ± 0.30°	4.47° ± 8.88°	3.59° ± 4.76°

4.4. Correlation Coefficient Analysis

The distributions of correlation coefficients comparing the sensor-to-vertical angle over individual gait cycles for body-mounted sensors vs. clothing-mounted sensors is shown in Figure 7. The box plots in Figure 7a indicate that the 'lower shank' and 'thigh' sensor pairs maintained a higher correlation than the 'waist' sensor pairs.

The mean correlation coefficient values are reported in Table 1. Values ranged from 0.97–0.98 for the lower shank and from 0.91–0.96 for the thigh, whereas the values for the waist were lower at 0.77 and 0.81.

In addition, there were notable outliers in the 'waist' sensor data from 'Participant 1' (Figure 7b).

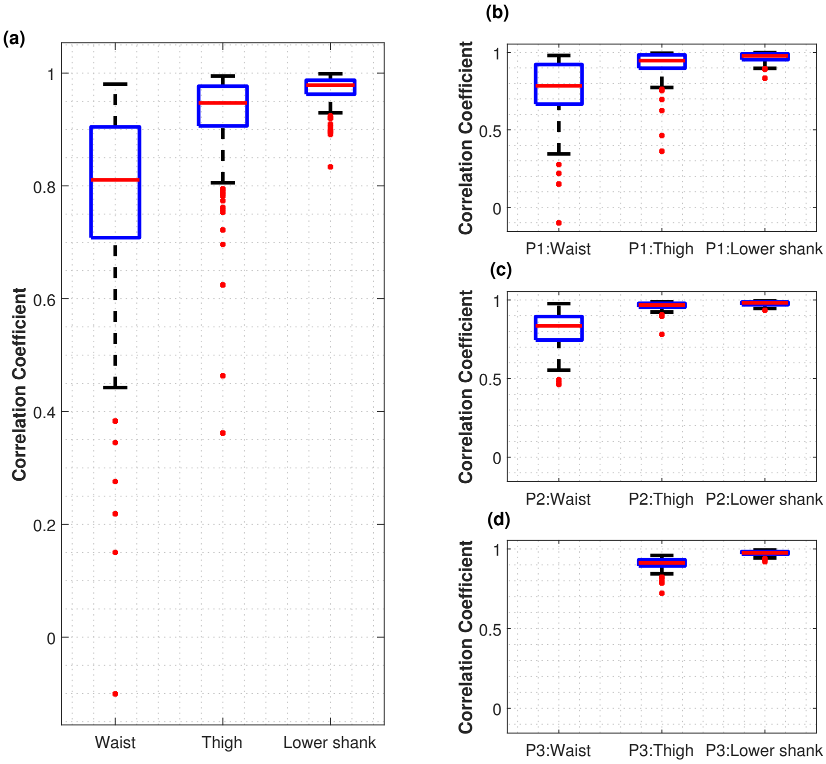

Figure 7. Correlations between the body-mounted sensor vs. clothing-mounted sensor in terms of their sensor-to-vertical angles over the course of a gait cycle. The plots show Pearson correlation coefficient values for (**a**) all 465 gait cycles, (**b**) Participant 1's data, (**c**) Participant 2's data and (**d**) Participant 3's data. P3 did not have a body-mounted 'waist' sensor.

5. Discussion

The main intention of this study was to examine how well data from multiple, frontal body-mounted sensors correlate with the data from lateral side clothing-mounted sensors with respect to 'walking' data and to find whether key gait related information can be extracted from the clothing-mounted sensors. From the overall analysis, it was possible to observe that even though the clothing data were not in full agreement with the body-mounted sensor readings, clothing data could be used to estimate and track useful gait information such as the IC, TO and MS points (Figure 3). Further, Figure 4, which shows the sensor-to-vertical angles for the left and right clothing-mounted sensors and for the right side body-mounted sensor on the lower-shank, shows that the lower shank gait information related to gait cycles are in close proximity in both data streams. Moreover, by examining Figure 4, it was noted that IC points from one leg (blue 'square') were approximately aligned with TO (black 'o') points on the other leg.

By simultaneously observing the angle changes in the waist, thigh and lower-shank sensors throughout the gait cycle as shown in Figures 4b–d and 5, the whole leg movement can be captured by the three angles, which would not be possible with only a single sensor.

Further, having the angles of the waist, thigh and lower-shank angles together can help with visualising the trunk, thigh and tibia movements, respectively. As Gao et al. explained [21], the angle information from the three sensors could potentially be sufficient for activity classification without the need for multiple heuristic features.

Figure 6c indicates that from IC to TO, changes of angular velocity seem to decrease slowly, while the angle along the vertical axis was being changed. This implies that this leg (right) was on the floor and the other leg (left) might be in swing phase, moving the body, which caused only the angle changes in the right leg. Figure 6b,c show quite similar changes in both sensors on body and clothing at stance phase (from 'green diamond' to 'blue o'). This pattern was noticed with all the other datasets as well. However, Figure 6a shows a slightly magnified shape of clothing-mounted phase portrait for body-mounted waist phase portrait. With some of the datasets, this incident was noted in the other direction, having a magnified phase portrait for clothing-mounted sensors.

From Table 1, it was noted that the body-mounted and clothing-mounted sensors had a mean angle difference of around 0° while the participants were standing, and it can be said that at the beginning of the data collection, the sensor pairs were at more or less similar orientations. Further, angle differences at the 'shank vertical' stage were comparatively lower than those at IC. This may have occurred as, at the 'shank vertical' stage, the clothing-mounted sensors were nearly at a resting state compared to the IC point, where there was an additional acceleration of the clothing.

There were also differences in the angle differences across participants, possibly due to differences in the clothing material and the fit of the clothing. For example, at IC, we saw larger angle differences at the lower shank for Participant 2, who was wearing loose cotton slacks, as compared with Participants 1 and 3, who were wearing jogging trousers with elastic at the ankles. Additionally, Participant 1's trousers were baggy at the thigh compared with Participant 2's, which could account for the larger angle difference observed in Participant 1's data at the thigh as compared with Participant 2's. We also noted that the orientation of the lower-shank sensors in the clothing could be affected by whether or not the participants were wearing shoes, and so putting on or removing shoes midway through data collection would affect the alignment between the body- and clothing-mounted sensors.

Figures 4–6 also indicated that clothing-mounted sensor data have a higher range of angle values than that of body-mounted sensor data. By observing the mean gait cycle shapes in Figures 4d–d and 5b with respect to both sensors (body-mounted and clothing-mounted), it can be further noted that clothing-mounted cycles had the same shape with an amplitude of data comparable to body-mounted data. Figure 5a shows the regularity of the walking pattern of this participant. Figure 5c–e also illustrates that each sensor pair had a similar shape with a higher range of values in clothing sensors. Figure 5b was drawn by taking into account the mean gait cycles from body- and clothing-mounted sensor data. Approximate IC and TO points for cycles were marked on the mean gait cycles to examine the stance and swing phases. Those angle variations could have happened due to looseness of clothing, as this can add additional movements, especially at the 'thigh' and 'lower shank' points when the person was walking with a higher acceleration. Even though an orientation correction mechanism was applied to the sensor data based on standing and walking segments (as mentioned in Section 3.3.1), sensors on clothing may have altered their positions.

However, Pearson's correlation coefficient analysis allowed interpretation of the data in a different way. Mean correlation coefficient values (Table 1) revealed that the waist sensor pair had the least correlation among all the participants, whereas lower shank and thigh had higher correlation values of more than 0.97. Yet, the waist sensor pairs also had a correlation above 0.76. These correlation coefficient values were further analysed based on the box plots shown in Figure 7. It was recognised that there were a few outlier values in waist sensor pairs. When examining the outlier data, it was noted that, at the point where a gait cycle occurred with a negative correlation coefficient value, both body-mounted and clothing-mounted signals deviated from the mean 'waist' gait cycle. However, the other two sensors had maintained the correlation at a higher level at that specific point. As both 'waist' signals had been changed at that point, it is possible that due to a hand movement or due to the band of the 'waist pouch', a sudden displacement of the sensors might have happened. Examining other outlier points, it was noted that clothing-mounted sensor data agreed with the mean gait cycle, while the body-mounted sensor data deviated from the mean gait cycle. This can be justified as the body-mounted sensor position might change slightly owing to the movements of the waist band of the trousers and the waist pouch because the trousers were worn nearly on top of the body-mounted waist sensor. Keeping the 'waist' sensor on the waist line of the trousers and waist-pouch band around the waist might have added additional movements or prevented the movements of the waist sensor. This may have caused the slightly lower correlation coefficient with respect to the sensor-to vertical axis angle than that of 'lower shank' and 'thigh' data. Hence, although the clothing-mounted sensors may not be a perfect representation of gait, the same can be said with the body-mounted sensors. Clothing- and body-mounted sensors have similar information content when considering gait (Figure 3a,b).

However, if the clothing is excessively loose or if the sensor is disoriented after doing the alignment, the results would not be as accurate as the expected results. However, even with that kind of subtle misalignment in the middle of the data collection, data would be able to give gait characteristics in a reasonable way (Figure 5). Wearing trousers that are not too loose-fitting near the lower shank/ankle and attaching the sensors firmly to the fabric to firmly fix their orientation would minimise these issues.

Future work includes using clothing-mounted sensor data in activity classification, using the structure of the gait as the feature that may improve the classification accuracy. Assuming that the clothing-mounted sensors are a feasible way of collecting data from people who have mobility disorders in an unobtrusive way, data could be collected for a longer period to analyse how gait patterns change due to factors such as fatigue, gait changes over extended periods of time, or changes of gait in response to a pharmaceutical, surgical or rehabilitative intervention.

6. Conclusions

In this study, we have collected and analysed data from multiple lightweight, time-synchronised sensors mounted into everyday loose clothing. Even though the data from clothing-mounted sensors showed a larger range of angle variation compared to that from the body-mounted sensors, the sensor pairs correlate well at key points in the gait cycle. The results also indicate that the data from the clothing-mounted sensors can be used in extracting and analysing the gait cycles in a productive way. Hence, we conclude that sensors mounted in loose clothing are a promising way of studying human movement.

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Chapter 7

Classifying Walking, Climbing Stairs and Turning using Loose Clothing-mounted Lower Body Sensor Data

As it was observed that the movement data were well correlated even with dynamic activities, this chapter explores how informative are the data collected from clothing-mounted sensors in activity classification by analysing data in different methods (based on sensor-to-vertical angles and phase portraits) in detail and comparing classification accuracies based on different features (heuristic i.e. sensor-to-vertical angle and non-heuristic features i.e. raw accelerometer and gyroscope data) and different classification approaches (machine learning and deep learning) for three cyclic gait patterns (walking, climbing up stairs, climbing down stairs) and turnings.

More figures that show the activity wise summary reports for each participant are listed as Appendix D.1.

Walking, climbing up and down stairs classifier accuracies were more than 90% in each approach while accuracy for turning classification were between 64.51% and 99.98%.

The results indicate that the loose clothing data are rich in information so that they can be used to distinguish gait related activities in a promising way.

7.1 Introduction

Human Activity Recognition (HAR) is challenging, yet, a popular research area which is widely being used in home-based health monitoring systems, video surveillance, gait analysis, falls detection, fitness tracking in athletes and gesture recognition systems [1, 2, 3]. Further, HAR can be applied on data in real-time [4, 5] or offline depending on the situation [6].

Mainly HAR systems obtain data from two sources, i.e. camera systems and sensors [2, 3]. These sensors can be further categorised into three sections such as body-worn sensors, object sensors (Radio-frequency identification (RFID) or accelerometers mounted objects) and ambient sensors [2, 7]. Camera/ video data can be analysed with computer vision techniques to recognise activities [3], while sensor data can be analysed with machine learning algorithms. Further, both video data and sensor data can be used to train Deep Learning (DL) models such as artificial neural networks (ANN), recurrent neural networks (RNN), convolutional neural networks (CNN) and long short term memory networks (LSTM). Conventional machine learning algorithms such as decision trees (DT), support vector machine (SVM), naïve Bayes (NB), K-nearest neighbour (KNN) and random forest (RF) achieve a significant progress in HAR [8]. Wearable body-worn sensor devices are popular in data acquisition in home-based monitoring systems and fitness tracking systems as they are capable of collecting data irrespective of where the person is, whereas video footage data are limited to a certain area.

Wang et al. [2] noted in their survey that most of the studies that were conducted in analysing 'Activities of daily living' (ADL) and sports activities used wearable sensors as they are capable of recording even slight movements with a higher sensitivity. Most of the activity recognition studies use a single point mounted wearable sensor [9, 10, 11] or smart phone [12, 13] in data collections.

However, Gao et al. [14] and Arif and Kattan [15] pointed out that the accuracy can be increased by using multiple sensors and Maurer et al. [4] also concluded their study in the same way as they used multiple e-watches on belt, shirt and trousers' pockets, back-pack and necklace in a real-time activity monitoring system. To increase the data analysis accuracy by mounting the sensors roughly onto the same place everyday and to make it easier for the wearer to put on multiple sensors easily, we suggest that it is better to mount sensors onto everyday wear clothing. Further, Van Laerhoven et al. [16] claimed that clothing is an optimal platform to mount multiple inertial measurement units (IMUs) to collect data from people in an unobtrusive way . Moreover, Michael and Howard [17] noted that sensors mounted onto clothing instead of strapping them onto a structure with rigid bands, gives better signal variations which helps to improve the activity recognition accuracy.

Taking into account the above mentioned arguments, this study investigates how informative these clothing mounted sensor data are, by visually representing the dynamic cyclical activities and how the gait-orientated activity classification accuracies work with shallow and deep learning algorithms.

7.2 Related Work

Conventional machine learning algorithms have successfully achieved a significant accuracy in HAR [8]. When using conventional approaches, features need to be extracted manually to train classifiers, whereas features will be automatically learnt from data in deep learning networks. Some arguments are there regarding the limitations of conventional machine learning methods with respect to model generalisation as the feature extraction highly depends on human domain knowledge for specific settings [2]. These shallow features are usually based on statistical features such as mean, average mean, standard deviation, average of standard deviation, skewness, average of skewness, kurtosis, average of kurtosis, variance, frequency, amplitude [2, 18] and such features usually work well with low-level activity classification [2]. Further, more labelled data are needed in training conventional models compared to deep learning approaches. Wang et al. [2] pointed out that conventional models work well with static data compared to dynamic activity data that should be taken as a data stream in training the networks.

DL networks are developed with more hidden layers than that of traditional ANNs. The more the hidden layers, the more the accuracy can be observed as the network can learn more from the dataset [2]. Most of the DL approaches use original signal directly in the network rather than extracting heuristic features [19, 20, 21, 22].

Even though DL networks are supposed to use raw data so that the network can study the features by itself, some studies have used heuristic data in deep neural networks [23, 24]. Vepakomma et al. [23] were able to categorise data into 22 activities at a reasonable accuracy, by using heuristic features extracted from a wrist worn accelerometer (mean and variance of magnitude of acceleration, mean and variance of first derivative of magnitude of acceleration, mean and variance of second derivative of magnitude of acceleration for 2 second time windows), gyroscope (mean and variance of magnitude of angular speed, mean and variance of first derivative of magnitude of angular speed, mean and variance of second derivative of magnitude of angular speed), ambient sensor and location (GPS) data. For their study they had used a conventional feed forward ANN with two hidden layers and had achieved more than 90% of accuracy for each activity classification. Walse et al. [24] had used dimensionality reduced features by applying principal component analysis (PCA) with an ANN i.e. 561 features generated by accelerometer and gyroscope data collected by a smartphone were reduced to 70 principal components. From this study, Walse et al. [24] have noted that even though the accuracy dropped by 2% compared to the ML approach with raw data, the training time was reduced when using the dimensionality reduced features with the network.

Arif and Kattan [15] used three IMUs on dominant wrist, chest and ankle on 9 participants to collect data from lying down, sitting, standing, walking, running, cycling, nordic walking, ascending stairs, descending stairs, vacuum cleaning, ironing clothes and jumping rope. 12 heuristic features were extracted from each axis of triaxial accelerometer data to do the classification in their analysis and a comparison was made among the activity classification accuracies based on KNN, rotation forest and back propagation neural network approaches. They concluded that rotation forest classifier with data from all three sensors was the best classifier to classify the activities.

Further, it is better to use a reasonable data sampling size for the training purposes with respect to gait cycles. Anguita et al. [25] and BenAbdelkader et al.'s [26] point was that the cadence (the number of steps per minute) for an ordinary person is 90 to 130 which results in a minimum of 1.5 (= 90/60) steps per second. Hence, they claimed that it would be better to have a time window larger than 1.5 s so that people with slower cadence should also get benefited in their analysis.

There are HAR studies conducted on clothing-mounted sensor data and some studies had used tight-fitting garments while others were based on loose clothing activity classification based on IMU data.

Gao et al. [14] had used multiple accelerometer based sensors in their study (classifying static activities, walking and transitions) and those sensors were fitted into a tight garment so that the sensors were on chest, left under-arm, waist and thigh. They compared the accuracy between single sensor and multiple sensors in HAR and observed how the accuracy changed based on different ML algorithms and different features. They used different features in time domain (Mean, variance), frequency domain (spectral energy, entropy) and other heuristic features (signal magnitude area, tilt angle). They concluded that multiple sensors let them achieve a higher accuracy with decision tree classifier with simpler features such as mean and variance of the signal.

In order to mimic collecting data from clothing for HAR Michael and Howard [17] used a pendulum and three different fabric materials (denim, jersey and roma) with three tri-axial accelerometers were used. The fabric was attached to the end of the pendulum and the three accelerometers were placed on three places such as one at the tip of the pendulum with a rigid band, the second one on the middle of the fabric and the third one at the end of the fabric. Then they collected data from the pendulum attaching a weight at the end of the pendulum and also removing that weight. They used SVM and discriminative regression machines (DRM) in classifications. Their conclusion was that the clothing mounted sensor data resulted in giving higher accuracy at the activity classification.

Gleadhill et al. [27] focused on the correlation of body-worn and tight fitting vest mounted sensor data on dead-lifting activity. As they focused only on a single activity and were using tight fitting clothing, they observed a reasonably high correlation between the body-worn and clothing-worn data.

Wu et al. [11] used a belt mounted waist accelerometer sensor in activity classification. They collected data from activities such as jumping, sitting-down, standing, running, walking, and falling from 7 subjects and used Discrete Wavelet Transform (DWT) to analyse the feature vectors with SVM. Their classifier output varied from 91.7% to 97.6%.

Kantoch [28] used a smart shirt with three sensors to classify sedentary behaviour. In their study, they used two features i.e. relative intensity of activity based on heart rate and variance of acceleration. They compared the accuracy based on six

ML approaches (linear discriminant analysis, SVM, KNN, NB, binary decision trees and ANN) and claimed that smart shirt data worked well with ML algorithms in recognising sedentary behaviour.

Using angle information in understanding gait related patterns is a common approach [29, 30, 31]. Wang et al. [30] analysed the plots for knee, thigh and shank angle for walking, climbing up and down stairs using body worn sensors. De Jong et al. [29] analysed the shank-to vertical axis angle in a study related to a foot orthotic. Wang et al. [30] used knee and hip angles to track the starting and end points of strides. In addition to them, Chen et al. [32] used phase portraits (signal as a function of its derivative) to observe the cyclic gait movement trajectories. They emphasised that those phase portraits were a productive visualisation tool that helped to observe the gait features such as regularity, stability and complexity as those closed trajectories denoted the periodic nature of the gait cycles marking sudden changes (sharp turnings) on them.

7.3 Materials and Methodology

7.3.1 Materials

The sensing system in this study consisted of 6 IMUs (based around the Bosch Sensortec BMI160 smart IMU) all using a synchronous bus, connected via flat ribbon cable forming a *"sensor string"*. Data collection procedure was described in earlier analyses [33] as well. Bespoke sensors were approximately 15×12×7mm each and had a combined weight of less than 18 g, and the inter-connecting cables weighed approximately 73 g. This sensor string was connected to a battery powered Raspberry Pi where the data was stored. The Pi and battery were worn in a waist-pouch attached with a belt. Data were sampled at 50 Hz. The range of the accelerometers was +/- 16 g with 12-bit resolution. The BMI160 IMU includes gyroscope, accelerometer and magnetometer readings.

The IMUs were attached inside clothing and on the body, so that there were six sensors along the both lateral sides of clothing covering the lower body (waist, thigh and lower shank). Sensors were taped securely along the seams of the clothing in the chosen position, and cotton bias binding was taped on top of the sensor string using double-sided tape for fabric as shown in Figure 7.1. In this way, the sensors were not outwardly visible and also not in contact with the skin which helped to make the system more comfortable for the wearer.

Figure 7.1: Sensor placement on clothing. There were six sensors along the lateral side of the lower body on both legs (waist, thigh and lower shank). Sensor strings were covered with bias binding as shown here in the right side.

7.3.2 Data Collection Procedure

Data collection procedure was the same procedure followed in our previous studies and it is explained in ([34]).Five healthy participants (age range: 28-48 years old; 3 males and 2 females) took part in the study. Each person selected a pair of trousers and a hoodie jacket in their usual size, and the researcher attached the sensors to the clothing. Four participants wore cotton-blend fleece jogging trousers, and one wore loose cotton slacks. Participants wore the clothing on three or four days for 5-8 hours per day of data collection. The Raspberry Pi and the battery pack were kept in a bag on the waist of the each participant.

On each day of data collection, participants were asked to perform a set of predefined activities to provide a ground truth, after which they then continued with their usual activities for the rest of the day. The ground truth activities comprised of two minute activities such as, (1) Standing still, (2) Sitting on a chair, (3) Lying on their back (supine position), (4), Sitting on the floor with legs outstretched, (5) Walking back and forth and (6) Climbing up and down stairs. The ground truth activities were video-recorded. For the rest of the day's activities, the participants were requested to keep a diary to log their activities.

7.3.3 Data Analysis

This study only focused on ambulatory related dynamic activities based on lower body mounted sensors and categorised those dynamic activities into four categories i.e. walking, climbing up stairs, climbing down stairs and turnings. For this analysis only the right hand side leg data from the trousers were used.

7.3.3.1 Pre-processing

Raw data were rotated twice using Rodrigues' rotation formula [35] to correct the orientations of the data so that the sensors were using right-handed coordinate system following ENU (East-North-Up) coordinate frame following the data alignment process described by Chakraborty et al. [36]. After the alignment correction the x, y and z axes measured the medial-lateral acceleration, anterior-posterior acceleration and the superior-inferior acceleration respectively. Then data were low pass filtered using a second-order Butterworth filter with a 3Hz cutoff frequency.

7.3.3.2 Phase Portraits and 3D Representation of Data

As walking, climbing up and down stairs movements are basically periodic movements, ‘phase portraits‘ were analysed to examine how well the clothing data reveal these movements. To generate phase portraits, gyroscope data (angular velocity) that represented movements in the sagittal plane were plotted against the sensor-to-vertical angles. These phase portraits represent the signal as a function of its derivative. That means the angular velocity (degrees per second) vs angle.

7.3.4 Activity Classifier

Activity classifiers were trained in both ways, i.e. with machine learning approach as well as in deep learning approach. Taking into account the reasons mentioned by Anguita et al. [25], data were sampled into 2 s time windows to train the networks.

Assuming that the significant movements in walking, climbing up and down stairs happen in the sagittal plane, the sensor-to-vertical angles that were projected to the vertical axis by the anterior-posterior axis of each sensor were used as the main feature vector to train the classifiers. These angles were calculated based on quaternion values. Quaternion values were estimated by using accelerometer, gyroscope and magnetometer data by using Madgwick algorithm [37]. Next, the sensor-to-vertical angles were calculated using the quaternion values following the algorithm described in our previous work [38]. The angles were defined in such a way that, if the leg is inclined, the angle will be negative, and if the leg is reclined, the angle is positive, as followed by Wang et al. [30].

For machine learning classifications 18 features were used to train the networks and the selected features were, moving variance of sensor-to-vertical angle for two second data windows from each sensor (3 features) , moving variance of gyroscopic data from the medial-lateral and superior-inferior axes for each sensor (2 axes $\times$ 3 sensors = 6 features) and moving variance of triaxial accelerometer data for each sensor (3 axis $\times$ 3 sensors = 9 features). From all the three axes of gyroscopic data, only the medial-lateral and superior-inferior direction gyroscopic data were used in the training, as walking, climbing up and down stairs happens in the sagittal plane around the anterior-posterior axis and turnings were expected to happen around the superior-inferior axis. Using MATLAB 'Classification learner', 6 classifiers were trained and they were decision trees, quadratic discriminant, Naïve Bayes, SVM, KNN and Ensemble. Each classifier was evaluated by a 5-fold cross validation method.

Under deep learning approach, recurrent neural network (RNN) type was used as RNNs can work well with temporal features while CNNs can perform well with spatial relationships [2]. Hence, LSTM network that is a type of RNN was used in this study as the DL approach. Two LSTM networks were trained with different sizes of feature vectors using raw accelerometer and gyroscope data and heuristic features. For one LSTM, moving variance of accelerometer and gyroscope data from waist, thigh and lower-shank were used. For the other LSTM network only 9 features were used, i.e. moving variance of sensor-to-vertical angle from each sensor (3 features), moving variance of gyroscopic data from the medial-lateral and superior-inferior axes for each sensor (2 axes $\times$ 3 sensors = 6 features). After that, data labelling was done for each activity i.e. walking, climbing up and down stairs and turnings, by using the video-ground truth data.

Both these LSTM networks consisted of five layers i.e. sequence input layer, LSTM layer, fully connected layer, softmax layer and classification output layer. LSTM layer was specified with 150 hidden units and the mini batch size was 50. Optimizer 'adam' was selected as it seemed to update the network in a stable manner [1, 39]. Both networks were evaluated by two techniques, i.e. leaving-one-subject-out method and using 25% of data in validation.

To examine the final output, in addition to this gait related activity classifier, another posture classifier was used from our previous work [33]. First, the data were classified into static and dynamic data based on 'moving standard deviation for magnitude of thigh data' for 2 second windows. Next, the static activities were categorised into four static postures. The four static postures were standing, sitting, lying down and sitting legs-outstretched. Three features were used in the posture classifier and they were moving mean of sensor-to-vertical angles over 1 s window from waist, thigh and lower-shank sensor [33]. The activity classifier was applied on the dynamic data that were identified by the above mentioned first classifier.

7.4 Results

7.4.1 Phase Portraits

First, the sensor-to-vertical angles for walking, climbing up and down stairs based on waist, thigh and lower-shank positions were examined to check how the clothing-mounted sensor data were able to interpret the information about these activities (Figure 7.2).

Next, phase portraits were analysed for three main periodic movements and Figure

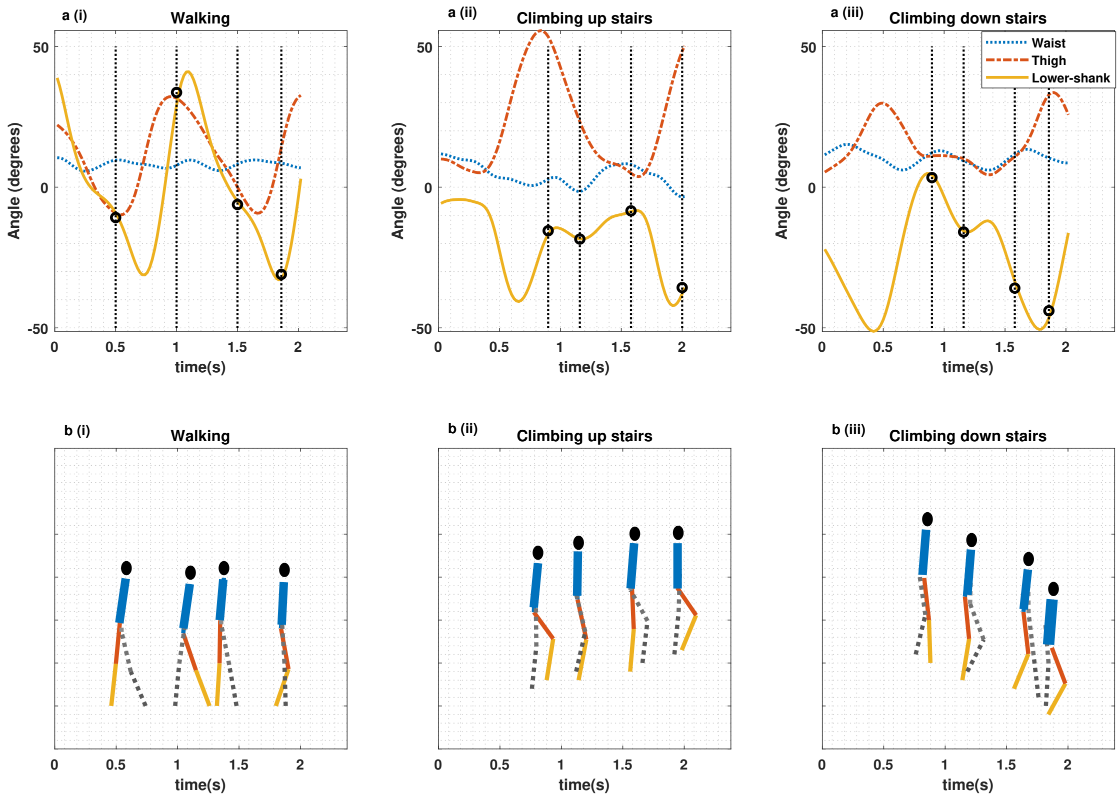

Figure 7.2: Sensor-to-vertical angle changes over different activities. Each plot shows 2 second data windows from each activity from each sensor on right leg (a(i)−a(iii)). Stick figures in bottom three plots (b(i)−b(iii)) are drawn using the angles (marked with a black dot 'o') from the top plots. Right leg angle changes in thighs are shown in red lines and lower-shank in yellow colour lines while left leg angle changes are shown in grey colour dotted lines.

7.3 depicts plots for walking, climbing up and down stairs with respect to waist, thigh and lower-shank sensor wise.

7.4.2 3D representation of Data

Sensor-to-vertical angles from waist, thigh and lower-shank were used to represent data in a 3D plot as shown in Figure 7.4. Four main postures are plotted on a 3D plot to examine how well dynamic movements happen in between the main postures. Figure 7.4 (a) shows 5 minutes of continuous data from video ground truthed data. This specific dataset started from five leg-raises followed by five sit-to stand cycles, lying down and sitting legs outstretched while sitting on the floor. Figure 7.4 (b)

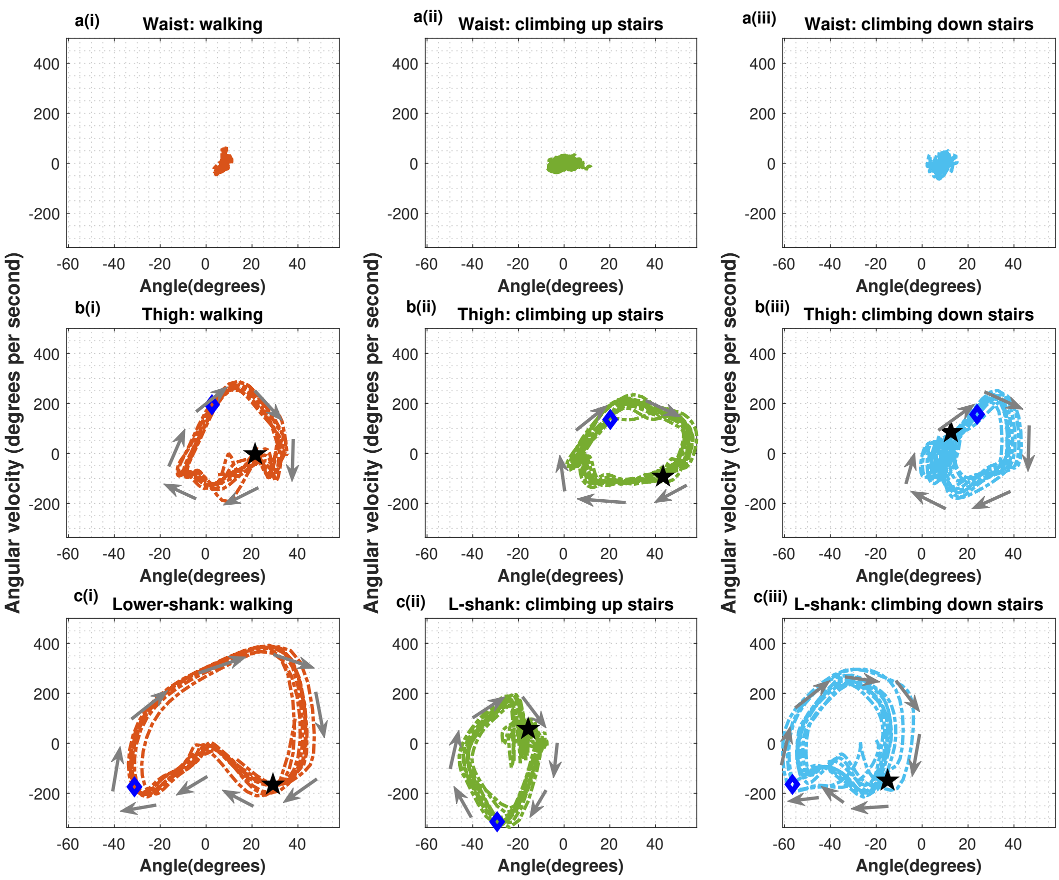

Figure 7.3: Phase portraits for different sensors for different activities i.e. walking, climbing up and down stairs for Participant 1 Day 2 data. Each plot roughly has 10s data from each activity. For a single cycle, approximate initial contact points (IC) in 'black stars' and toe-off (TO) points in 'blue diamonds' are marked on each phase portrait.

shows how standing up data is surrounded by walking, climbing up and down stairs data.

7.4.3 Representation of 'Turning' in Gyroscopic Data

Gyroscope data that represented movements along the sagittal plane provided information on walking, climbing up and down stairs. Further it was noticed that to capture 'turnings', vertical axis of gyroscopic data could be used as it had significant pattern changes at turnings. Figure 7.5 shows the data pattern relevant to turnings with respect to different axes of gyroscope.

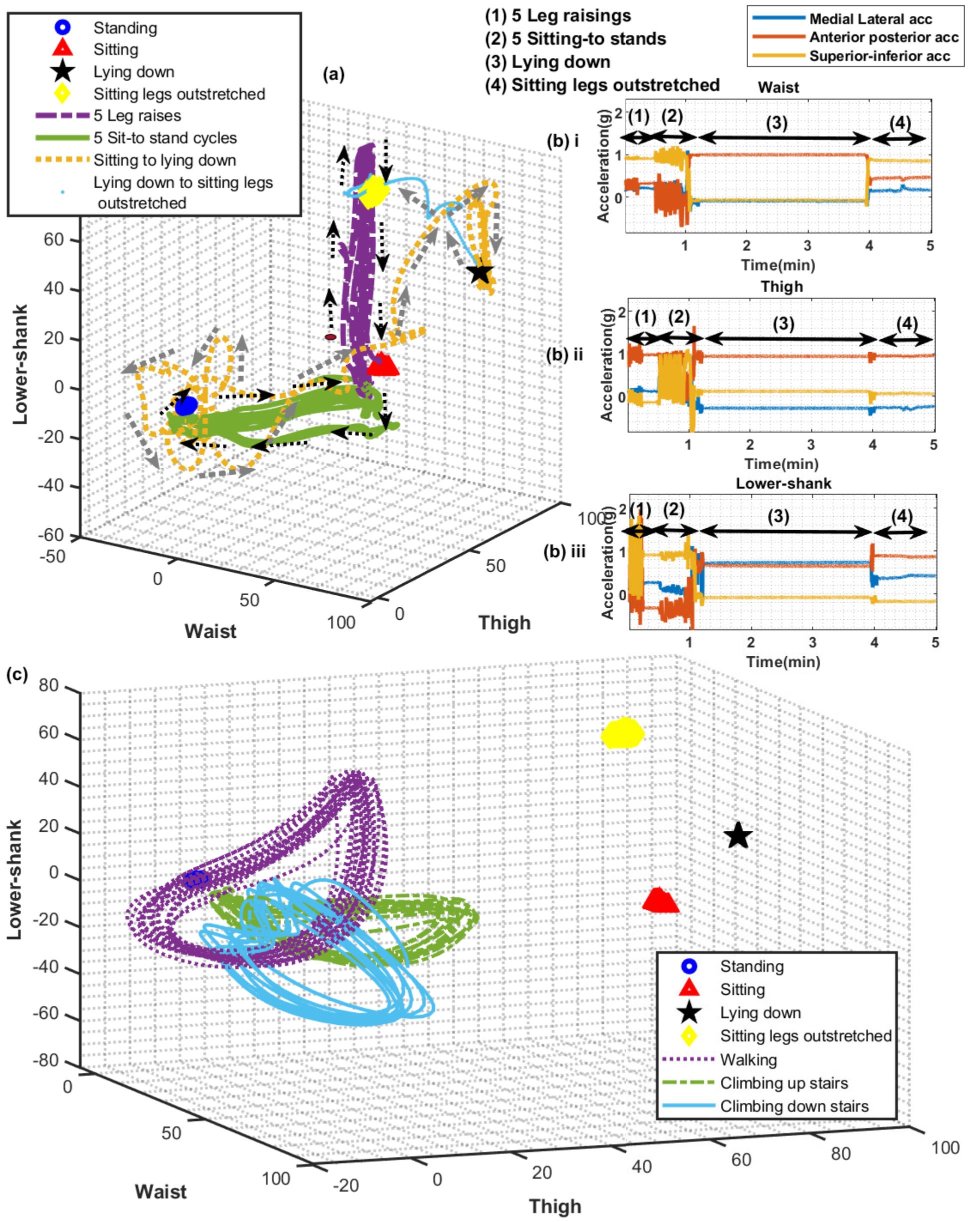

Figure 7.4: 3D representation of sensor−to−vertical angles for main postures and activities from Participant 1 Day 2 data. Four main postures standing, sitting, lying down, sitting on the floor are marked on the 3D plot taking waist, thigh and lower−shank angles as the x, y and z axes respectively. (a) shows five minutes of data including 5 leg−raises while sitting one a chair (purple dashed line); 5 sit−to stand and stand−to sit cycles (green line); transition from sit−to stand and then lying down (orange dotted lines to black star); and lying down to sitting with legs outstretched (cyan line). (b) i− b(iii) shows the raw accelerometer data from waist, thigh and lower-shank for the activities on plot (a). Plot (c) shows roughly 15 s of data from walking (purple dotted line), climbing up stairs (green dashed line) and climbing down stairs (cyan line) on the 3D plot and it can be seen that they are scattered around standing posture (blue dot).

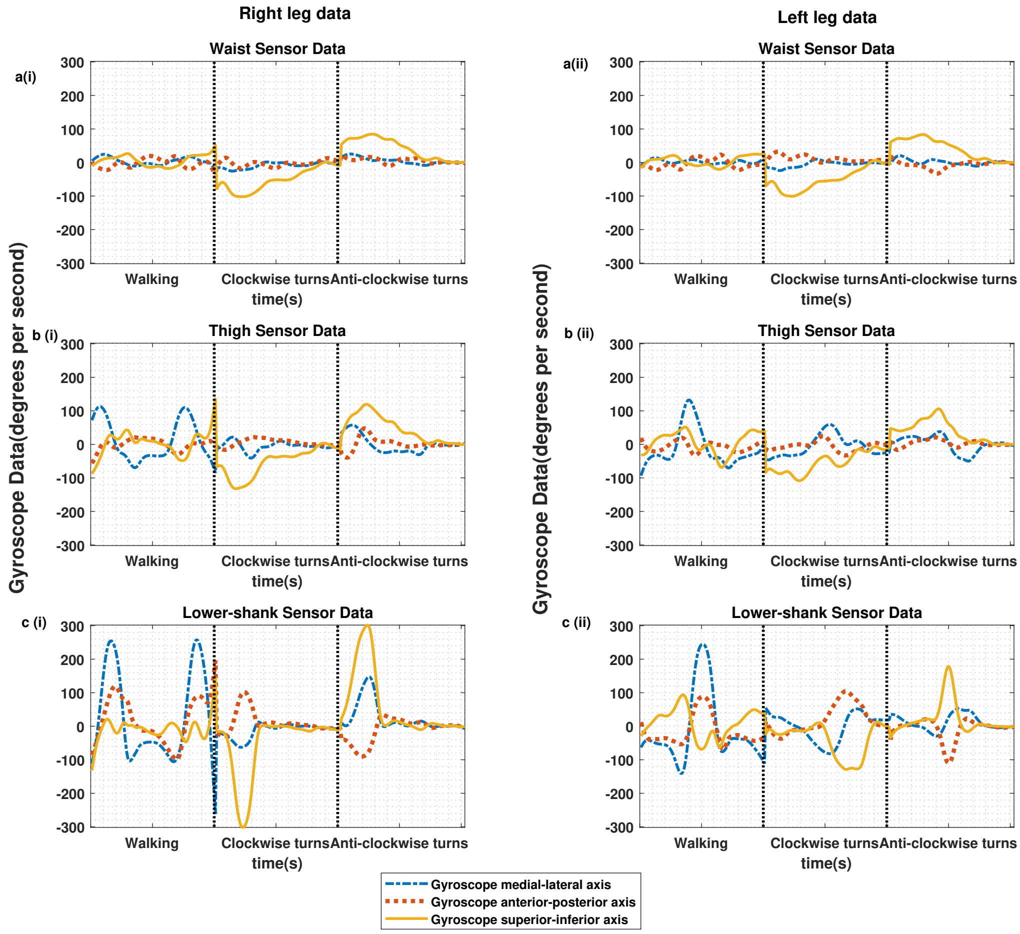

Figure 7.5: 'Walking' and 'Turning' on gyroscope data from Participant 2 Day 2 dataset. Each plot represent two second data from walking, clockwise turning and anti-clockwise turning data with respect to gyroscope data. Plot (c) shows that more details such as direction of turnings could be distinguished by the superior-inferior/vertical axis (yellow line) of shank gyroscope data. Movements on the sagittal plane such as walking could capture with medial-lateral gyroscopic data (blue dashed line).

7.4.4 Activity Classifier Output

Accuracies for activity classifiers generated from ML and DL approaches are shown in Table 7.1.

Figure 7.6 shows a visual representation of the final classification output obtained by using the LSTM with 9 features for one of the datasets.

Classifier	**Walking**	**Climbing up stairs**	**Climbing down stairs**	**Turning**	**Overall Accuracy**
Fine tree	98.2%	97.00%	98.83%	89.54%	97.50%
Quadratic discriminant	99.2%	98.04%	98.50%	76.53%	97.00%
Naïve Bayes	94.92%	91.50%	96.13%	64.51%	91.70%
Cubic SVM	99.94%	99.90%	99.97%	97.38%	99.80%
Fine KNN	100%	99.97%	99.98%	99.91%	100%
Ensemble	99.99%	99.94%	99.98%	99.91%	100%
Deep Learning					
LSTM with 9 features	99.37%	96.89%	94.01%	84.10%	97.01%
LSTM with all raw accelometer and gyroscope data	99.53%	97.82%	94.00%	78.82%	97.01%

Table 7.1: Accuracy comparison for different types of activity classifiers. Leaving-one-subject-out validation method was applied in calculating the accuracy of the classifiers in preparing this table. Except for classifying 'turnings' with Naïve Bayes classifier, other classifiers had accuracy levels greater than 78% for each activity.

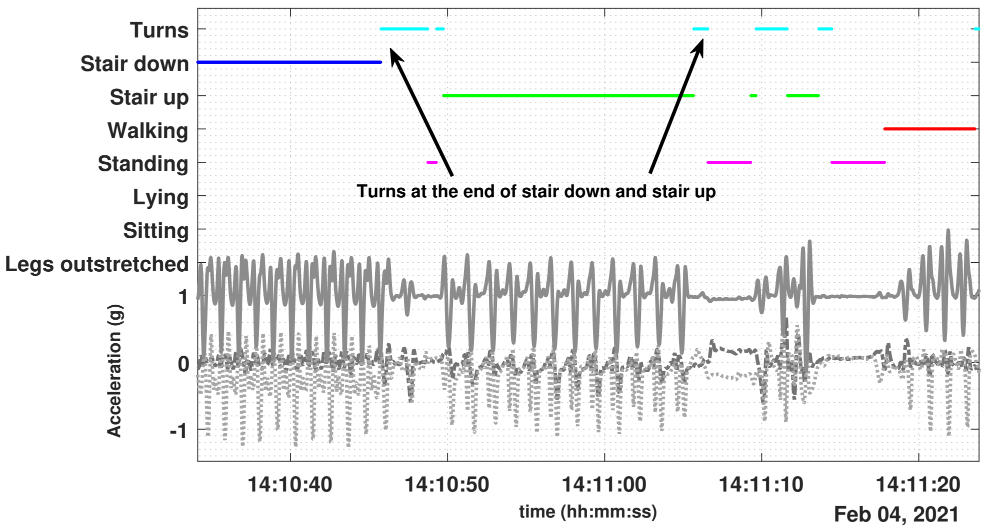

Figure 7.6: A zoomed out section from the activity classification output. Activity classification outputs are marked on the top of the graph along with the lower-shank acceleration values (grey-colour lines). A 'climbing down stairs' segment (blue line) followed by a turning, standing up (waiting)) and climbing up stairs followed by another turning and standing/waiting segment can be seen on the figure.

7.5 Discussion

As shown in Figure 7.2, thigh and lower-shank plots agreed with Wang et al.'s plots [30]. Stick figures on bottom plots in Figure 7.2 were generated using the angles on the top three plots in Figure 7.2. These stick figures resemble actual walking, climbing up and down stairs patterns. Hence, it can be said that the clothing-mounted sensors are also capable of capturing the movements up to a reasonable extent.

Phase portraits can also be provided promising results under three activities as shown in Figure 7.3. When rough toe-off and initial contact points were marked on lower-shank walking data following the methodology mentioned in [38], it was noted that ‘walking’ phase portraits for shank presented by Chen et al. [32] agreed with our plot. Compared to the shank phase portrait, the thigh phase portrait for ’walking’ lay between a smaller angle range which was sensible according to the bio-mechanics of walking.

When comparing the average angle changes from all the 15 participant-days worth dataset, it was noted that thigh angles ranged from $-10.1° \pm 7.0°$ to $25.9° \pm 6.6°$ while lower-shank angles varied from $-32.3° \pm 8.7°$ to $36.7° \pm 6.8°$. Waist sensor data lay between $1.0° \pm 4.5°$ and $10.2° \pm 4.6°$ as waist slightly reclines from vertical axis while walking.

When it comes to the ‘climbing up stairs’ data with ‘lower-shank’ data, it can be clearly noticed that the angle range was between $-33.9° \pm 9.5°$ and $1.4° \pm 6.3°$. That indicated the inclined movement of the lower-shank with respect to the vertical axis. Moreover, initial contact area can be noticed with a peak near $0°$. On the other hand, thigh movement for ‘climbing up stairs’ ranged angles from $-0.6° \pm 3.7°$ to $47.1° \pm 11.2°$ because, the thigh reclines with ‘climbing up stairs’ movement making positive angles (Figure 7.2). Similar to ‘walking’ angle range at the waist, angle changes in ‘climbing up stairs’ at the waist also vary in a smaller range i.e. from $-1.8° \pm 5.0°$ to $11.7° \pm 12.1°$.

It can be said that, the lower-shank phase portraits were also rich in information for ‘climbing down stairs’ movement. As expected, ‘climbing down stairs’ cycles consisted of broader sensor-to-vertical angles and smaller reclining angles that ranged from $-42.9° \pm 9.0°$ and $12.4° \pm 9.2°$. Similar to ‘climbing up stairs’ data with thigh sensor, ‘climbing down stairs’ data were also positive angles as the thigh reclines always when stepping down. Thigh does not move back and forth as in walking, making positive and negative angles. The ‘thigh’ angle ranges were from $6.0° \pm 3.7°$ to $33.2° \pm 7.1°$ while the ‘waist’ sensor had a smaller angle range (from $4.0° \pm 2.8°$ to $13.5° \pm 3.6°$) for ‘climbing down stairs’ activity as well.

Plot (a) in Figure 7.4 shows five sit-to stands (green lines) and leg-raises (purple dashed lines) (while sitting down) in a 3D plot. Clothing data could examine the transitions between the standing posture (blue cluster) and the sitting posture (red cluster) while the participant was performing the sit-to stands. Similarly, the leg-raises while sitting down on a chair (purple dashed lines) data segments moved from ‘sitting’ (red cluster) to ‘sitting legs outstretched’ (yellow cluster) posture. Sit-to stands (green lines) ended somewhere closer to the red dot (roughly at $-20°$) indicating that the lower-shank was inclined as a result of keeping the legs in a slanting position without keeping them in a vertical position.

Plot (c) in Figure 7.4 shows how walking, climbing up and down stairs can be illustrated in a 3D plot using three clothing worn sensors. These periodic movements are centred around the standing data (blue cluster) and these closed trajectories demonstrate the regularity of the cyclic movements.

As depicted in Figure 7.5, ‘turnings’ were able to be clearly captured with vertical axis of gyroscope data. Not only turnings, but also the direction where the turning was made could be distinguished by the vertical axis of the lower-shank gyroscope data. In Figure 7.5, lower-shank data shows how the ‘turnings’ are made clock-wise (negative angular velocity) and anti-clockwise (positive angular velocity) with respect to gyroscope data.

Finally, after observing the movement data based on different features, the activity classifiers implemented with different approaches were compared. Under machine learning concepts, six different accuracy levels were compared i.e. fine tree, quadratic discriminant, Naïve Bayes, SVM, KNN and Ensemble and under deep learning concepts accuracy levels of two LSTM networks were compared. Table 7.1 shows the accuracy levels in identifying each activity.

In each approach, walking, climbing up and down stairs achieved a reasonably high accuracy levels than that of ‘turning’ classification accuracy. Most of the ‘turnings’ extracted to do the evaluation were not slow turnings and they were in between walking back and forth data segments. To train the networks, two second time windows were used and if there were sudden turnings while walking they were classified as walking. That could be the reason for the misclassifications in identifying such ‘turnings’. However, if quick ‘turnings’ needed to be identified at a higher accuracy, classifier training window sizes can be minimised as gyroscope data could clearly distinguish ‘turnings’ from usual activities.

When training LSTM networks, it was noted that the LSTM with 9 features reached the maximum accuracy in less than 60 epochs while the other network with more features reached the maximum accuracy after 100 epochs. LSTM with 9 features was also able to classify the activities up to a reasonable extent similar to the LSTM trained with raw accelerometer and gyroscope data. Even though we are unable to identify the best type of the classifier with this limited dataset, by analysing these accuracies a conclusion can be derived as these clothing-mounted sensor data can be used successfully in activity classification either with machine learning or deep learning approaches with appropriate feature vectors.

Figure 7.6 shows how the classifier output worked on a dataset. At the beginning of Figure 7.6, there was a segment of a climbing down stairs followed by a turning, climbing up stairs, turning and standing. Further, before the walking segment (magenta colour line) at the end of Figure 7.6 there were turnings and ‘climbing up stairs’ segments which were verified with the video data.

7.6 Conclusions

Usage of bio-mechanical wearable sensors (including accelerometer, gyroscope, magnetometer, pressure sensor, and vibration sensor) is a usable technique to monitor mobility of people outside clinical or laboratory settings at an acceptable cost. As multiple sensors can be used in increasing the classification accuracy, multiple sensors can be mounted into clothing, to make the sensor wearing process easier. This study analysed three sensors attached to lateral seam of the trousers near waist, upper thigh and lower-shank to investigate how informative were the clothing data in terms of classifying gait related activities, mainly based on sensor-to-vertical angles as the main feature.

Even though the data were collected from loose clothing-mounted sensors, it was noted that these data were rich in information as they were able to represent the actual movements with stick figures by using sensor-to-vertical angles. Moreover, phase portraits drawn with these data can be used in analysing high level details of the quality and speed of the gait patterns and they can be used to check the regularity of the cyclical movements.

Higher activity classification accuracies on both machine learning and deep learning approaches in this study can be justified as sensor-to-vertical angles and gyroscope data seemed to have distinguishable patterns for walking, climbing up and down stairs and turnings.

By considering these factors we conclude that the sensors mounted onto loose clothing can be used successfully in activity classification as well as in extracting information about periodic ambulatory movements.

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Chapter 8

General Discussion

The aim of this thesis was to investigate the possibility of using loose clothing-mounted sensor data over extended periods with a view to eventually using them as a home based healthcare monitoring system. In order to quantify and understand the human movements, five key objectives were achieved i.e. validating how loose-clothing mounted sensor data correlate with body-mounted sensor data by using Actigraph sensors as a feasibility study, conducting the main data collection that consists of a semi-natural dataset with clothing-mounted lightweight sensors, implementing a posture classifier with multiple sensor data, validating how clothing-mounted and body-mounted sensor data with respect to walking data and implementing a gait related activity classifier based on the lower-body data. This chapter discusses how these aims were achieved, while recapitulating the objectives of the research. Further, this chapter discusses the limitations of the work.

8.1 Discussion

8.1.1 Objective 1: Feasibility study for collecting data from clothing mounted sensors

The first study was a feasibility study involving the use of COTS sensors to collect data from the clothing. Actigraph sensors were used in this study as the COTS sensors. The housing of the Actigraph sensors meant that they were easily wearable on the body with bands. In addition to that, they were also able to attach into the clothing, sewing the bands into clothing, maintaining the same orientation approximately. This feasibility study paved the way for the understanding that even though the body-mounted and clothing-mounted signals were different to each other, a reasonable level of accuracy could be achieved in activity classification with clothing-mounted sensor data. There were subtle misclassifications in the activity classifier that could have been improved by applying an improved filtering (low-pass) mechanism to the signals and using multiple sensor data in the classifier feature vector.

Further, this study clearly indicated that when the clothing were not too loose, a reasonable correlation could be observed between body-mounted and clothing-mounted sensor data, even for dynamic movements such as 'walking'. For static postures such as standing and sitting, the correlations between the two signals were usually higher for clothing which were not too loose. However, it was noted that it would have been better to use light-weight sensors in clothing in order to increase the accuracy of the data, as sometimes these sensors tended to drag the clothing due to the weight of the Actigraphs (19 grams).

Moreover, the first pre-processing task performed here, was correcting for the time lag between body-mounted and clothing-mounted sensors. The time lags may have occurred due to two reasons i.e. there could be synchronisation issues with the internal clocks of the Actigraph devices and additional movements that happen with the clothing dynamics. It was supposed to correct only the time-lags that occurred owing to the synchronisation of the internal clocks, in order to check whether clothing data had started capturing an activity before or after the body-mounted data. However, both of the above mentioned time-lags were corrected at the same time, as it was not feasible to correct them separately in this feasibility study. Hence, in order to overcome the internal clock synchronisation issue, a set of synchronised light-weight sensors were used in the main data collection in this research.

In addition to the above mentioned insights, this data collection performed with Actigraph sensors were used to set up the minimum and maximum acceleration range for the new set of light weight accelerometers that were planned to be used in the next data collection so that they can be used to cover the accelerations that are expected to measure during day-to day activities.

8.1.2 Objective 2: Main data collection that consists of a semi-natural dataset based on clothing-mounted light-weight sensors

One primary intention of this thesis was to investigate the potential of using loose clothing-mounted sensor data in home-based long-term healthcare monitoring systems. Hence, the ultimate goal of this work was to check how reliable and feasible the clothing-mounted multiple sensor data were, in interpreting without any ground truth data for extended period of time.

Based on the conclusions derived on the previous analysis (Objective 1), bespoke light-weight sensors were used in this data collection in relation to objective 2 and they were connected to a Raspberry Pi via a flat ribbon forming *sensor strings* so that all the sensors were time synchronised. The 12 IMUs were able to cover the whole body of the participants. However, this thesis only describes the data collected from the lower body.

Currently, there are publicly available datasets that help in Human Activity Recognition (HAR). Almost all these databases are based on smartphone data [1, 2, 3, 4] and body-mounted sensor data [5, 6]. The present data collection was a semi-natural dataset (data from predefined set of activities with video ground truth and data from usual day-to-day activities along with diary data) collected from clothing mounted IMUs.

Even though there were only 5 participants taking part in the data collection, altogether in the end, there were 15 participant-days worth of data as they wore the clothing with sensors for 1-4 days. These data were collected during the weekdays and at weekends from some participants so that it could be clearly observed how the activities would change at weekends compared to weekdays.

This main data collection contains data from accelerometers, gyroscopes and magnetometers. Hence, there is an opportunity for creating various handcrafted features in improving classifier accuracies. Further, as the dataset includes ground truth data for activities such as 'sitting-to stands', 'turnings' and 'leg raising', researchers who are interested in analysing transitional activities and postures can use these data in analysing them.

8.1.3 Objective 3: Postural classifier based on clothing-mounted sensor data

The study conducted under Objective 1 found that the clothing-mounted data correlated well with the body-mounted sensor data with respect to static postures such as 'standing' and 'sitting'. Hence, a posture classifier was implemented using the multiple clothing-mounted sensors. As the first step, the data were categorised into static and dynamic activities based on the 'thigh' data. The waist, thigh and lower-shank/ ankle sensor to vertical axis angles were used as the feature vector for the posture classifier.

This posture classifier had a 100% accuracy as the training and testing data points were manually selected (highly-selected) by the researcher based on the video data and this accuracy seemed to have declined with data from natural activities such as sitting with the legs crossed and slouch positions. As three sensors were used in this analysis, the data could visually be represented in a 3D plot considering waist, thigh and lower-shank/ankle inclination angles as x, y and z axes of the plot respectively. That plot was used to observe how the data-clusters corresponded to each posture scattered on the 3D plot. As the clusters were in clearly separable sections, it explains achieving a high accuracy in the posture classification with these features.

However, when the classifier output was compared with the diary data of the participants, some mismatches were noted. Some segments of the data marked as 'sitting' on the diary data were classified by the classifier as 'sitting on the floor with legs outstretched' posture. The reason for this was identified by observing the angle changes across the sensors. It was noted that only the lower-shank/ankle data had changed its inclination angles at these segments. When comparing those inclination angles, it was obvious, why those data segments were classified as 'sitting on the floor', because the lower-shank/ankle inclination angles were close to 70°. When the inclination angle goes beyond 70°, that indicates the leg is inclined and it is almost in the horizontal plane.

Further, it was observed that there was a notable percentage of a 'lying down' segment during a weekday for one of the participants. As this particular participant was a sedentary office worker, it was unlikely to be a 'lying down' posture. When the data was compared with the diary data, it was noted that the participant was 'sitting' while keeping the legs on the desk. In this situation, all the angles (waist, thigh and lower-shank/ankle) were beyond 65°, indicating that the participant was 'lying down'. This type of misclassifications could have been corrected adding information from the upper-body.

Further, it was explained how different window sizes can be used in creating feature vectors in different scenarios. As this study was totally based on posture classification, sudden movements/transitional movements were neglected. Hence, a 3 second window size was used in generating feature vectors for this study. However, it was noted that when there is a requirement in identifying transitions, it is better to use smaller window sizes as of 0.5 second or 1 second.

Finally, it can be said that a significant percentage of daily activities of ordinary people (who do not engage much in physical activities) can be captured by postures and they can be identified by the lower body data.

8.1.4 Comparing Body-mounted and Clothing-mounted Sensor Data in terms of 'Gait' Data

The data from the feasibility study conducted with the Actigraph sensors indicated that it would be better to use light-weight sensors in clothing as mentioned earlier. As one aim of this work was to check how informative the clothing-mounted sensor data with respect to human movement were, the correlation between the body-mounted and clothing-mounted gait cycles were estimated to validate the data.

Frontal side body-mounted sensor data were compared with the lateral side clothing-mounted sensor data to compare how the lateral side movements correlate with respect to the frontal side. In this research, 'mid-swing' (right before the initial contact) points were used as the starting point of a gait cycle. These 'mid-swing' points were identified by using the magnitude of the lower-shank/ ankle accelerometer data. Although the algorithm could identify the 'mid-swing' points from the body-mounted data at a 99.67% accuracy, the accuracy in identifying 'mid-swing' points with the clothing-mounted data was 97.87%. It was noted that some turning points were taken as 'mid-swing' points in clothing-mounted data. However, the algorithm could have been improved by using gyroscope data to check whether the identified 'mid-swing' points were 'turnings' or not (Chapter 6). When the correct 'mid-swing' points were identified, the Initial Contact (IC) and Toe Off (TO) points could be identified correctly using the gyroscope data.

When visually comparing the left and right hand side angles changes of the lower-shank/ankle for 'walking' data, it was noted that at the ICs the Sensor to Vertical Angle (SVA) angles were positive and gradually the angles reached 0°, indicating that the foot was flat. After that, the angles became negative indicating that the leg behind was having an inclination at the TO points. The IC points and TO points in left and right hand legs could be seen having a synchronisation mimicking the actual walking data as expected.

When comparing the angle differences between the two sensors when the participants were stationary i.e. 'standing up', it was clear that the sensors were pretty well aligned as the angle difference was less than 2°. However, when the participants were walking, the angle differences were higher, especially at the thigh and lower-shank/ankle (7° - 20°) while at the waist the angle difference was 6° - 8°. However, when the mean correlation coefficient values were compared between the sensor pairs, it was noted that the 'thigh' and the 'lower-shank' sensor pairs were correlated more strongly than the waist sensor pair. When further analysing these values with box plots, it was noted that there were a few outliers in the waist sensor pair which might have reduced the mean correlation value between waist sensor pairs. Such outliers could potentially have been avoided if there was no waist pouch with a band on top of the sensors. Either the Raspberry Pi and the battery pack could have been kept in a pocket or a wireless data transmission technique could have been used instead of using the Raspberry Pi around the waist.

Finally, by analysing the 3D representation of the data and phase portraits, it can be clearly seen that even though the clothing-mounted sensor data were having a wider range of data than that of the body-mounted data, they both follow the same shape. Further, it can be clearly seen that the mid-swing, IC and TO positions were aligned with the body-mounted sensor data with a smaller gap, paving a way to have a rich dataset to perform a productive 'gait analysis'.

8.1.5 Activity Classifier Based on Lower Body Data

After establishing that the body-mounted and clothing-mounted sensor data are reasonably well-correlated for 'walking' data, the clothing-mounted sensor data were further analysed with respect to gait related activities i.e. 'walking', 'climbing up stairs' , 'climbing down stairs' and 'turnings'. These data were analysed using 3D plots and phase portraits based on inclination angles and gyroscope data to examine how the Initial Contact (IC) and Toe Off (TO) points can be seen on the phase portraits with respect to the bio-mechanics of walking. In addition to that, these activities were classified with Machine Learning (ML) and Deep Learning (DL) techniques with different types of heuristic (sensor-to-vertical angles) and non-heuristic features (row accelerometer and gyroscope data).

It was noted that the inclination angles can be used to derive conclusions such as whether the body/limbs were inclined or reclined with respect to the vertical axis. Hence, these angles can be used to picture the postures of the people, for example, whether the people have been sitting properly or in slouch positions with respect to the waist, thigh and lower-shank/ ankle sensors. Moreover, Figure 2 in Chapter 7, was an example to indicate that these inclination angles were able to reflect the movements of the people. Those stick figures seemed to be tallied with the bio-mechanics of the relevant activities.

Further, it was noted that the phase portraits were useful in analysing the cyclic movements, as they were able to clearly show whether the angles of the cyclic movement had been constantly maintained throughout a walking/ going up stairs/ going down stairs phase. In addition to that, the marked IC and TO points on the cycles can be explained with respect to the bio-mechanics of the movements. As phase portraits can be used to check whether the same shape of the pattern could be maintained constantly within the person to examine their walking pattern and this approach was sensitive to detect angle changes between individuals as it has good potential for detecting differences due, for example, to movement disorders.

In addition to the above mentioned 2D plots, the data were plotted on 3D plots taking waist, thigh and lower-shank/ankle angles as the x, y and z axes respectively. The 3D plots were able to show clearly how the movements happen in the 3D space and the transitions happen changing from one posture to another. For instance, 'walking', 'going up stairs' and 'going down stairs' movements were scattered around the standing posture while the 'sit-to stand' movements were changing the postures from 'sitting' to 'standing' and 'leg-raising' movements were changing the postures from 'sitting' to 'sitting on the floor legs outstretched' postures.

Besides the cyclic movements, 'turnings' were also analysed in this study using the gyroscope data collected from the clothing-mounted sensors. It is promising to see that these loose clothing-mounted data are rich in such information. Even though the classifier accuracies were not high for the identification of turnings, it could be due to the window size (2 s) used in this training dataset. For training purposes, 2 s window sizes were selected in this study. However, most of the 'turnings' happened during the 'walking' back and forth data segments and they seemed to have happened in under a 1 s. In order to analyse more about turnings, the window size of the training data can be adjusted.

Finally, by analysing the activity classifier accuracies, it can be said that, other than the turnings, almost all the other activities had reasonably high accuracies (greater than 94%) irrespective of the training mechanism (ML or DL). When comparing the number of epochs needed to train the LSTM networks, it was noted that the network that was trained with 9 features (inclination angles and gyroscope data) reached the highest accuracy in 60 epochs, while the other network which was trained with all the accelerometer and gyroscope data needed 100 epochs. However, as this study was conducted with data from 15 participant-days worth of data, a conclusion cannot be derived to emphasise which set of features or which type of learning mechanism was best to be used in the training purpose. Nonetheless, based on this analysis, it can be concluded that these loose clothing-mounted data can be used in activity classification as well to derive information to analyse data with respect to movements.

8.2 Limitations

In this thesis, a few limitations were identified in several stages such as in the sensor attachment process to the clothing, data pre-processing mechanism, data collection equipment and data annotation process.

As the sensor strings were attached to the inner seam of the clothing, the initial orientation of the sensor relative to the limb and to the world is unknown. Hence, an orientation correction method was applied to the dataset. Orientation correction is performed at the beginning of the data collection based on the standing up right data segment. This set up had a possibility of disrupting the orientation of the sensors if the clothing position was changed in the middle of the data collection. For instance, there is a high chance of disrupting the orientation of the sensors, especially the lower-shank/ ankle sensors, after wearing or removing the shoes. This may affect the orientation correction mechanism and then the classifier accuracy.

When it comes to the data collection procedure, it was noted that some of the waist sensor readings were affected by the waist band of the waist-pouch. Body-mounted sensor position might change slightly owing to the movements of the waist band of the trousers and the waist pouch because the trousers were worn nearly on top of the body-mounted waist sensor. Keeping the ‘waist’ sensor on the waist line of the trousers and waist-pouch band around the waist might have added additional movements or prevented the movements of the waist sensor. Nevertheless, this issue can be solved by adopting a wireless data transmission instead of having a battery powered Raspberry Pi on the waist.

The number of participants can be also considered as a limitation in this research. As this research was based on data from 5 participants it can be said that it would have been better if more participants had been involved in this data collection. If so, there would be more data from different sizes of people and wider range of data for different activities could have been collected to train the classifiers. Nevertheless, this data collection was conducted extensively and systematically and there were more than 90 hours of data in the entire data collection.

When it comes to the usability of these clothing, when a user wants to wash the clothing, it was found that it was easy to remove the sensor string and the piping in one attempt. However, after washing the clothing, the sensors have to be attached again placing the sensors on the correct positions. This process was not so difficult, yet, it can be improved. There is a possibility of attaching smaller velcro strips on the places where the sensors have to be mounted and can have velcro at the back of the sensors too.

References

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Chapter 9

Conclusion and Future Work

The broader aim of this thesis was to investigate the possibility of using loose clothing-mounted sensor data over extended periods with a view to eventually using them as a home based healthcare monitoring system. The motivation behind this was to investigate whether the loose clothing data was informative enough to analyse people's everyday movements by generating systematic reports so that eventually such reports can be used by clinicians and wearers so they get benefited. This chapter completes the thesis with an overall conclusion explaining the main contribution and possibilities for future work.

9.1 Conclusions

Mounting wearable sensors into loose clothing is a reasonable move to establish home based healthcare monitoring systems especially for people with movement disorders. Mounting sensors on clothing can be explained as a controlled way of placing the sensors as they can be kept in proportion to the limbs so that they will not be able to slide down/ dislocate or cannot be worn upside down and the orientation will be known up to a certain extent. In addition, some participants may find it easier to put on and take off loose clothing. Hence, sensors mounted in loose clothing would be a practical and convenient way of analysing human movements. It is a favourable and unobtrusive technique as clothing is an ideal platform to have multiple sensors at once so that a clear picture of movements can be derived from the data. The first intention of this study was to quantify these clothing data and next, to understand the clothing data with respect to human movements.

This thesis was able to validate how the loose clothing-mounted sensor data correlate with body-mounted sensor data with respect to static postures as well as dynamic movements such as 'walking'. Even though these clothing-mounted data seemed to have higher accelerations than that of body-mounted data, as clothing dynamics add additional accelerations to the movements, they correlate well with each other's signals. The results indicated that the clothing data also can be used in extracting and analysing the gait cycles in a productive way.

In order to understand the human movements with these loose clothing data, mainly, the sensor-to-vertical angles (sensor-to-vertical angles) of the sensors were studied in this research. This research was based on a less number of heuristic features as there were data from multiple sensors. Stick figures and 3D plots were drawn with the data collected from these multiple sensors. Only using the lower-body mounted sensors, the stick figures were able to reflect the whole body movements, representing the trunk, thigh and tibia with the use of sensor-to-vertical angles with respect to waist, thigh and lower-shank/ ankle respectively. This reveals how productively these multiple sensor data can be used in reflecting human movements. Further, these clothing data emphasise their reliability with the phase portraits that were drawn to check the gait regularity.

By plotting all these data in a 3D space with respect to the sensor-to-vertical angles of waist, thigh and lower-shank/ankle sensors, the transitions from one posture/activity to another such as sit-to stand and leg-raises (sitting to sitting legs outstretched) could be observed clearly. Hence, it can be emphasised that these data can be used productively in analysing the human movements in between the basic postures.

As these data showed high accuracies in classifying the data into static postures and dynamic activities in both Machine Learning (ML) and Deep Learning (DL) approaches, it can be said that these loose clothing-mounted sensor data can be used effectively in activity/ posture classifications as well. Finally, a conclusion can be arrived at that multiple loose clothing-mounted sensor data can be used in quantifying and understanding human movements based on IMU data, as they are capable of reflecting the movements with less number of meaningful heuristic features such as sensor-to-vertical angles.

9.2 Future Work

Further analyses are possible with these data in many ways. First of all, even though data were collected from both the upper and lower body, this thesis only analysed the data from the lower body. There is the potential to classify a greater number of activities, with the inclusion of the data from the upper body.

There are possible improvements that can be added to the existing analyses. For example, the posture classification was limited to analysing only the angles disregarding whether that was an inclining or a reclining movement with respect to the vertical axis. Using a different method in calculating the angles, they can be analysed within the range of 0° to 360°. There is a possibility of extending this analysis even to study sleeping postures such as supine, prone, left and right positions. Moreover, transitions and turns can be analysed by picking up smaller window sizes from the data to analyse quick movements. When the window sizes of the data is changed, different information can be extracted from them as shown in Chapter 5.

There is another possibility of analysing phase portraits for people with movement disorders to check their upper and lower limits of the sensor-to-vertical angles with respect to their gait cycles. Following the same procedure, another dataset could be collected from people with movement disorders and can produce the phase portraits. These portraits could provide insights about individual differences in walking patterns, and how they progress over time.

Appendices

Appendix A

Appendices for Chapter 4 - Ethical approval

SBS 19-20 31 **School of Biological Sciences**

Ethics Committee - Project Approval

Principal Investigator(s)	Prof. William Harwin
Other researchers involved	Prof. Faustina Hwang, Udeni Jayasinghe (student)
School/course/other	NA
Title of project	'A technical feasibility study of long-term activity monitoring using wearable sensors mounted in clothing'
Submitted	16/01/20
Referred to Head of School	31/01/20
Stage 1	16/01/20 – sent to one other committee member
Stage 2	23/01/20 – minor concerns of the committee sent to the applicants
Stage 3	27/01/20 - revision received
Stage 4	31/01/20- recommendation to approve passed on to HoS and applicants informed

Chair of Ethics Committee:	Dr M. Alejandra Perotti
Date:	31/01/20
Head of School:	.... Prof Phil Dash
Date:	4/2/20

SBS21-22 18

School of Biological Sciences
Ethics Committee - Project Approval

Principal Investigator(s)	Prof. William Harwin
Other researchers involved	Prof. Faustina Hwang, Udeni Jayasinghe
School/course/other	NA
Title of project	'**A technical feasibility study of long-term activity monitoring using wearable sensors mounted in clothing (Amendment)**'
Submitted	06/05/22
Referred to Head of School	10/05/22
Stage 1	06/05/22– sent to one other committee member
Stage 2	06/05/22– minor concerns of the committee sent to the applicants
Stage 3	09/05/22- revision received
Stage 4	10/05/22- recommendation to approve passed on to HoS and applicants informed

Chair of Ethics Committee: Dr M. Alejandra Perotti

Date: 10/05/22

Head of School: Prof Phil Dash

Date: 10.05.22

Appendix B

Appendices for Chapter 5

B.1 Moving standard deviation for waist vs thigh for different time windows.

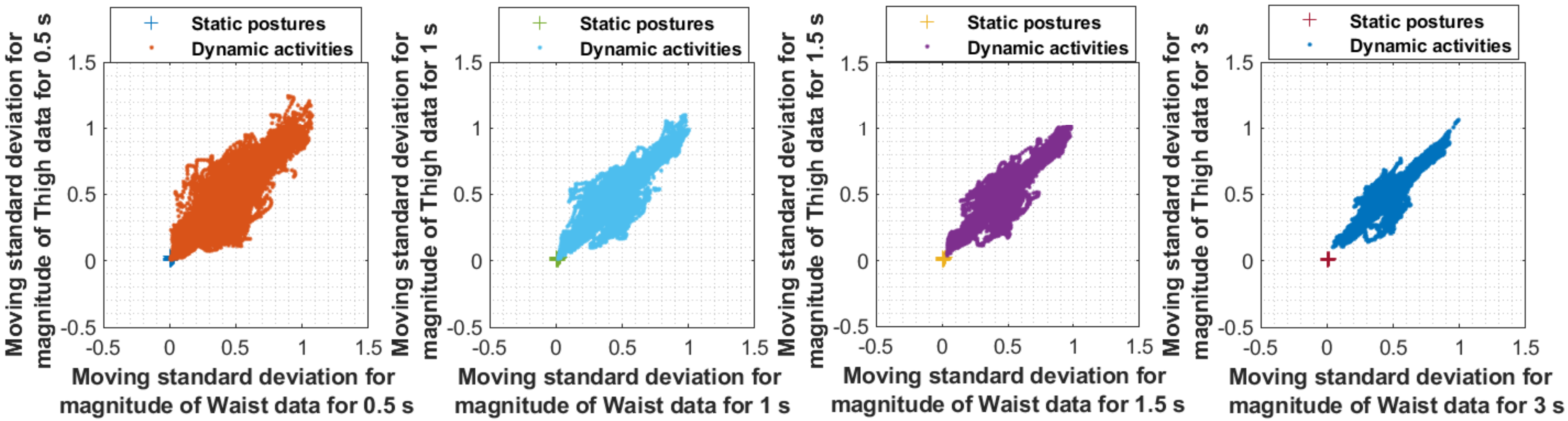

Figure B.1: Moving standard deviation for Waist data against Thigh data for static vs dynamic activities for different window sizes. On the top two plots, overlapping can be observed in static and dynamic clusters and on the other hand on the bottom two plots, it can be noted that a decision boundary line can be drawn separating the two clusters.

B.2 Moving standard deviation for thigh data for each dataset for different time windows

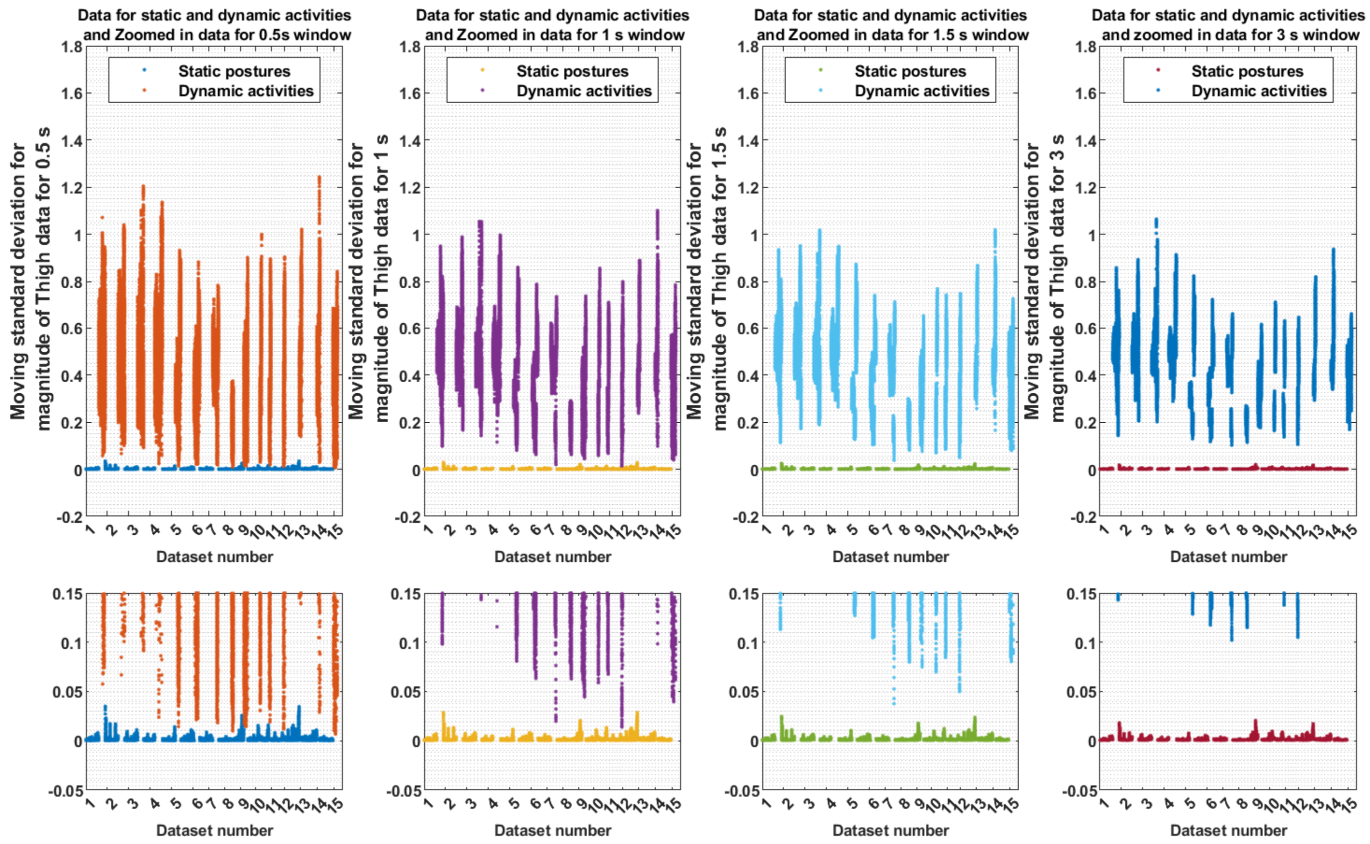

Figure B.2: Moving standard deviation for magnitude of Thigh data for static vs dynamic activities for different window sizes for all the 15 datasets. On the top four plots, overlapping can be seen and on the other hand on the bottom four plots no overlapping can be seen with in the two clusters.

Posture classifier outputs for the "usual activities" for the rest of the day (i.e. non-ground truthed activities) for each participant are given below.

B.3 Posture wise summary reports for the participants

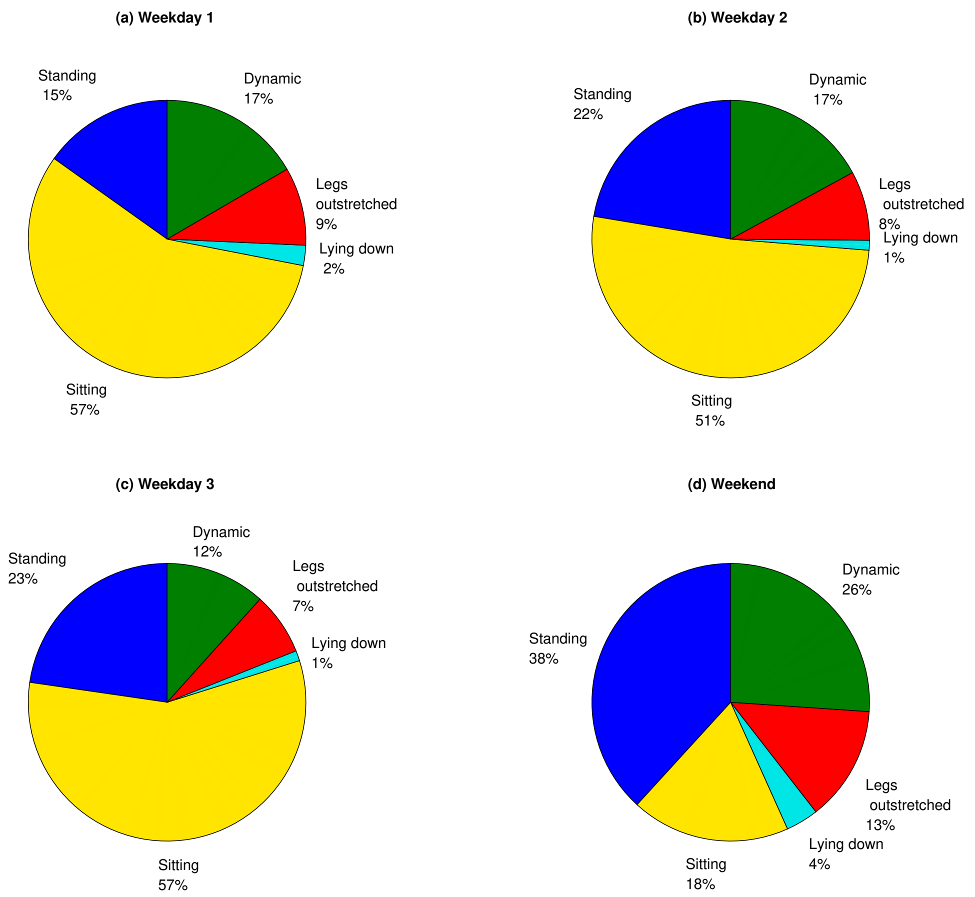

Figure B.3: Four days' activity summary report for 'Participant B', based on analysis of the sensor data. This includes three weekdays and one weekend day. Compared to weekdays, there was more standing and dynamic movements at the weekend. Also, the participant was sitting most of time during the weekdays with less time spent in dynamic movements.

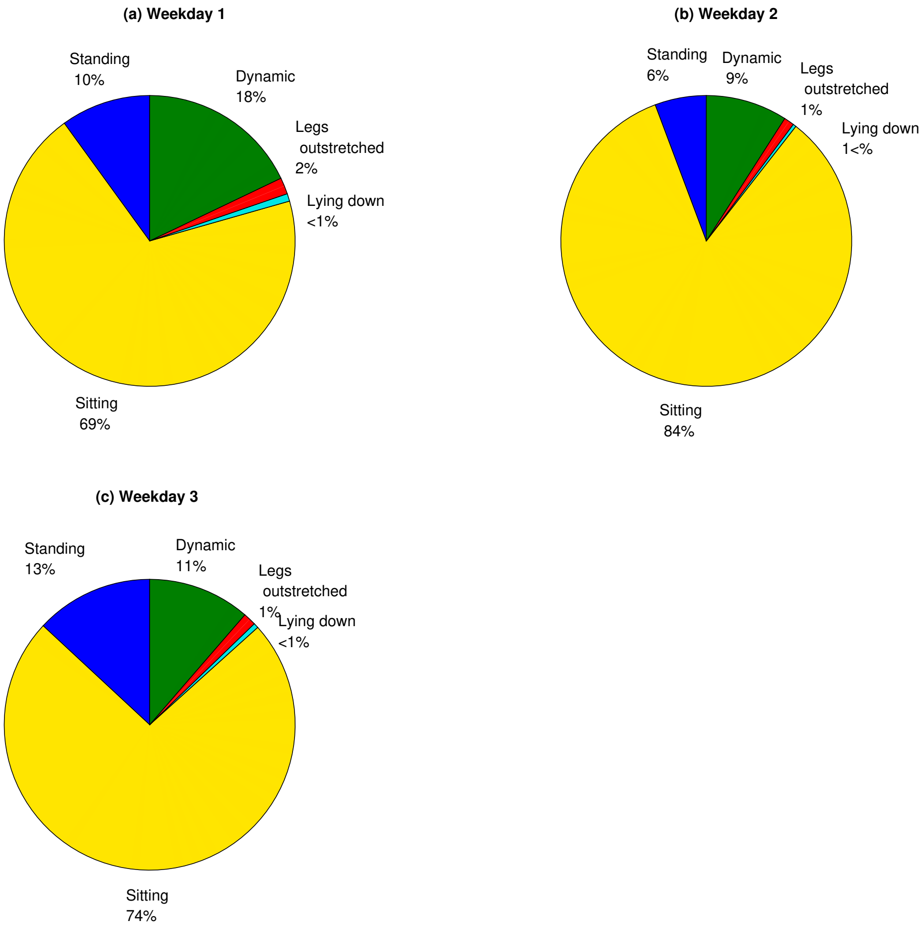

Figure B.4: Three days' activity summary report for 'Participant C', based on analysis of the sensor data. This includes three weekdays. This participant was sitting most of time during these days compared to the other participants.

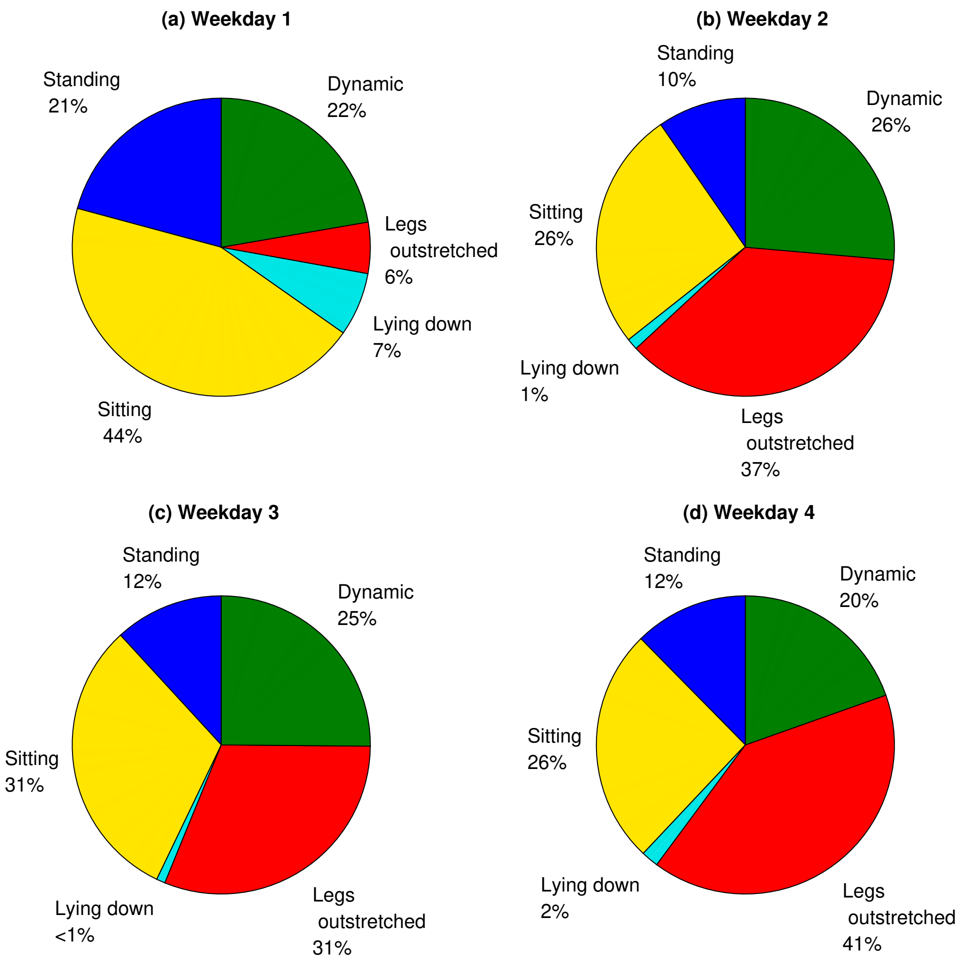

Figure B.5: Four days' activity summary report for 'Participant D'. This participant took part in the data collection during four weekdays. Compared to the other participants, this participant had been engaged in a higher proportion of dynamic activities and standing (32% - 43%).

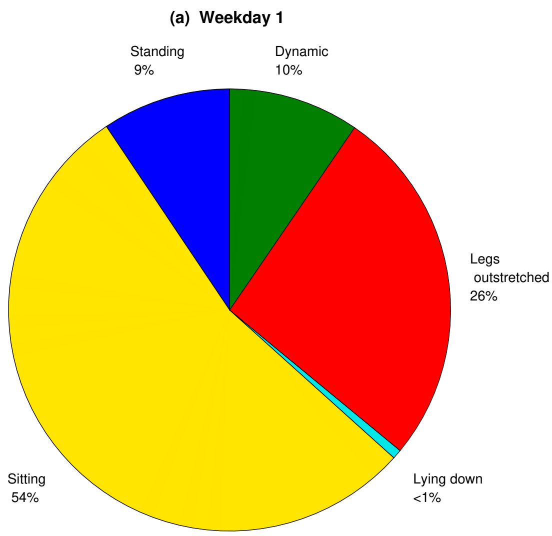

Figure B.6: The activity summary report for 'Participant E'. The participant took part in a single working day. The participant was sitting most of time during the day.

Appendix C

Appendices for Chapter 6

C.1 Mean gait cycles for the participants

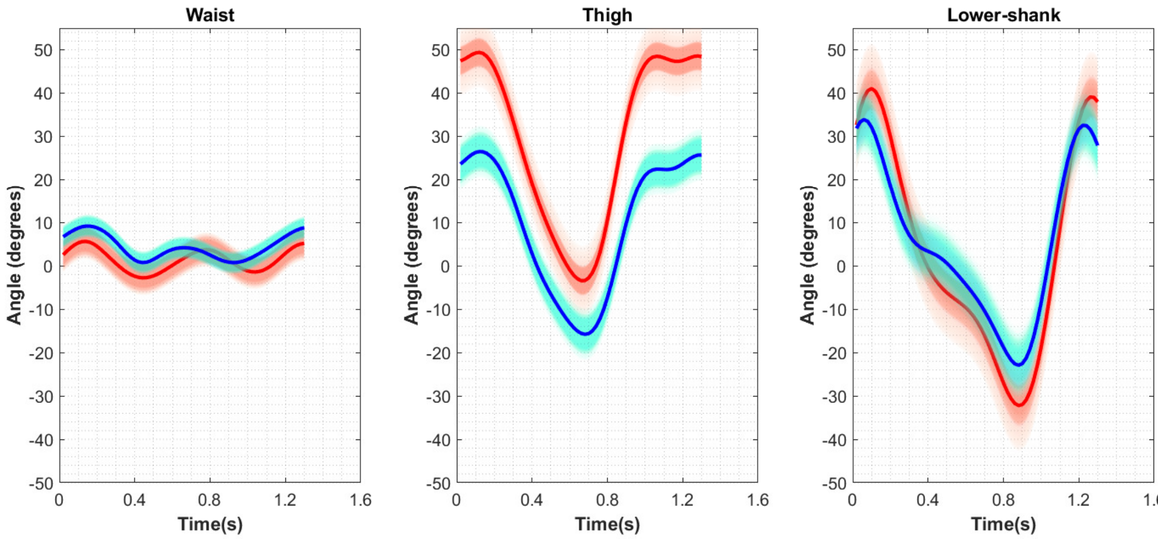

Figure C.1: Mean gait cycles for waist, thigh and ankle sensors from 'Participant 1-Day1. Body-mounted (red) and clothing-mounted (blue). Shaded areas on figures represent the standard deviation information.

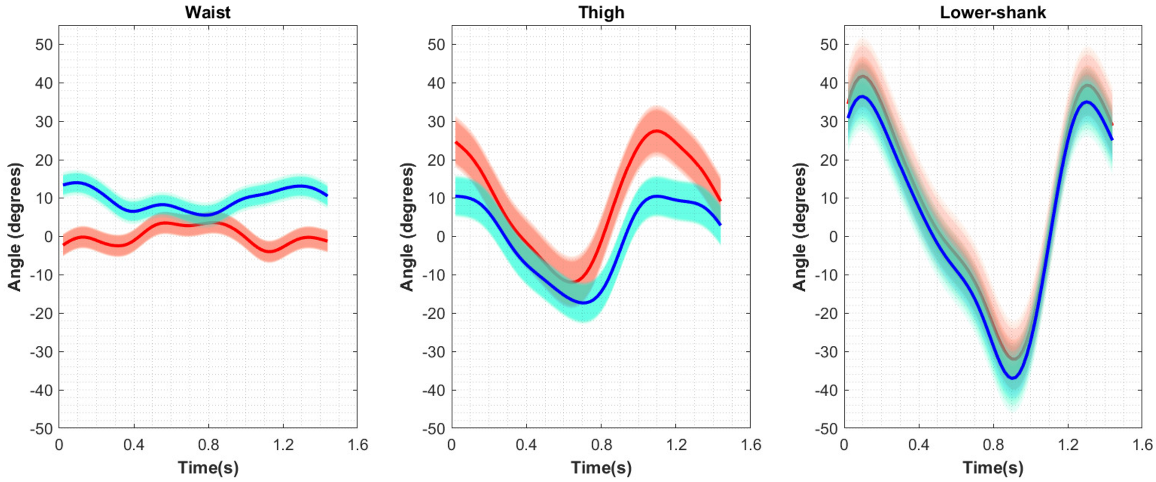

Figure C.2: Mean gait cycles for waist, thigh and ankle sensors from 'Participant 1-Day2. Body-mounted (red) and clothing-mounted (blue). Shaded areas on figures represent the standard deviation information.

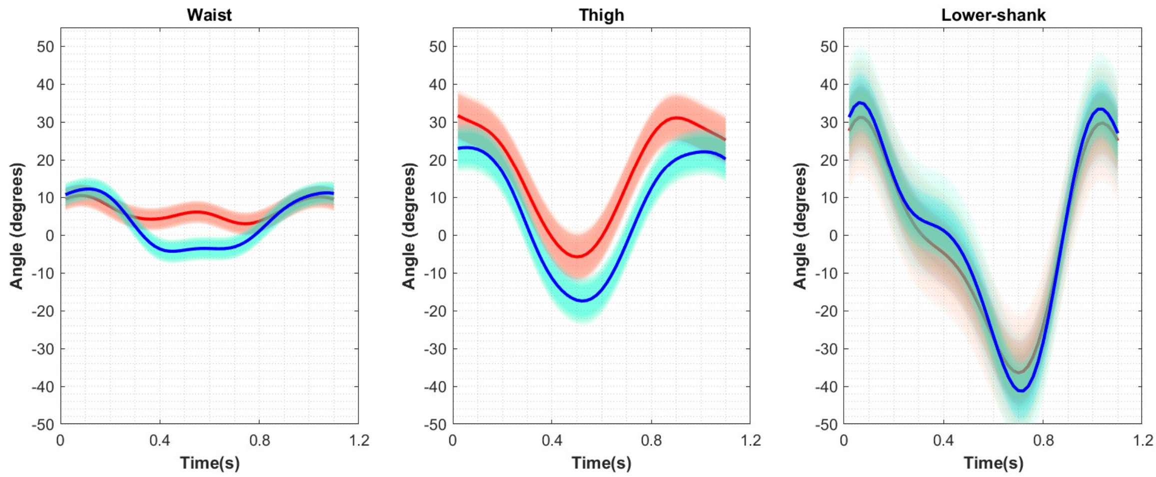

Figure C.3: Mean gait cycles for waist, thigh and ankle sensors from 'Participant 2-Day1. Body-mounted (red) and clothing-mounted (blue). Shaded areas on figures represent the standard deviation information.

67 gait cycles and mean gait cycle from both body-mounted and clothing mounted sensors from Participant 2 Day 2. Data are shown in Figure C.4. As mentioned earlier (sub-section 3.3.2 in Chapter 6), Figure C.4 (c)-iii shows that the mean angle changes in body-mounted lower-shank sensor shape agrees approximately with the inverted shank-to vertical axis angle data presented in De Jong and et al.'s study [**?**].

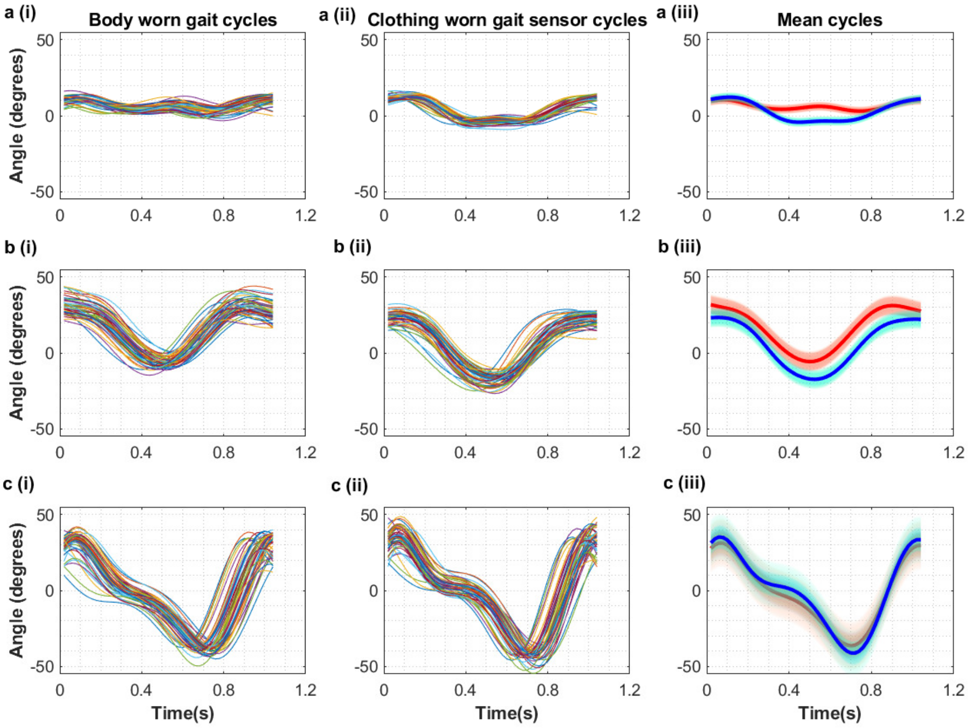

Figure C.4: Angle changes for 67 gait cycles and mean gait cycles for one of the participants for both body-mounted and clothing mounted sensors. These graphs depict angle changes for gait cycles of (a) i. waist body-mounted, (a) ii. waist clothing-mounted, (a) iii. mean waist gait cycle for body-mounted (red) and clothing-mounted (blue), (b) i. thigh body-mounted, (b) ii. thigh clothing-mounted, (b) iii. mean thigh gait cycle for body-mounted (red) and clothing-mounted (blue), (c) i. lower-shank body-mounted, (c) ii. lower-shank clothing-mounted, (c) iii. mean lower-shank gait cycle for body-mounted (red) and clothing-mounted (blue). Shaded areas on figure (a) iii, (b) iii and (c) iii represent standard deviation information.

C.2 3D representation of the gait cycles for the participants

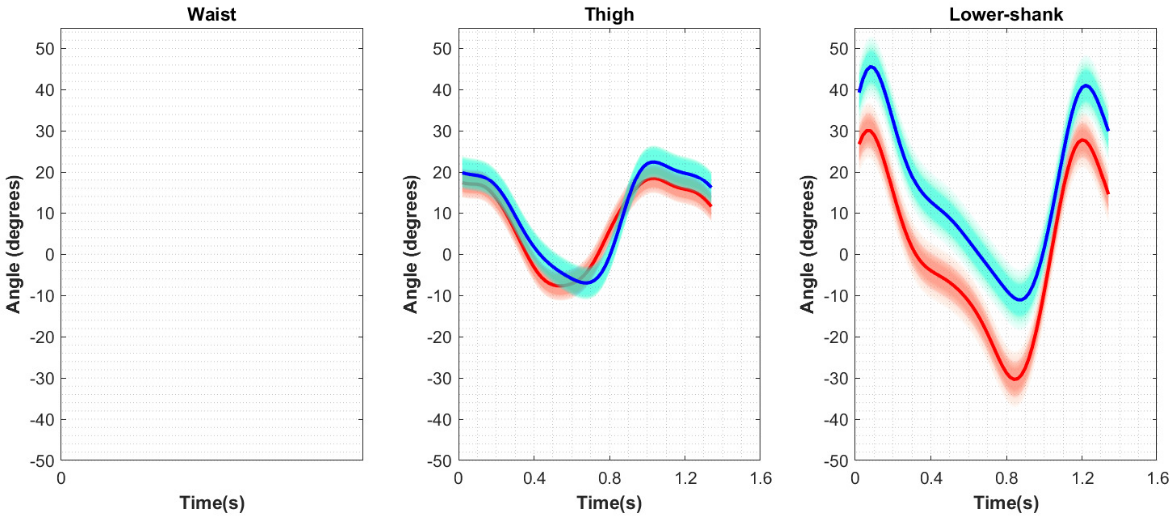

Figure C.5: Mean gait cycles for thigh and ankle sensors from ‘Participant 3- Day 1. Participant 3 did not wear a waist sensor pair. Body-mounted (red) and clothing-mounted (blue). Shaded areas on figures represent the standard deviation information.

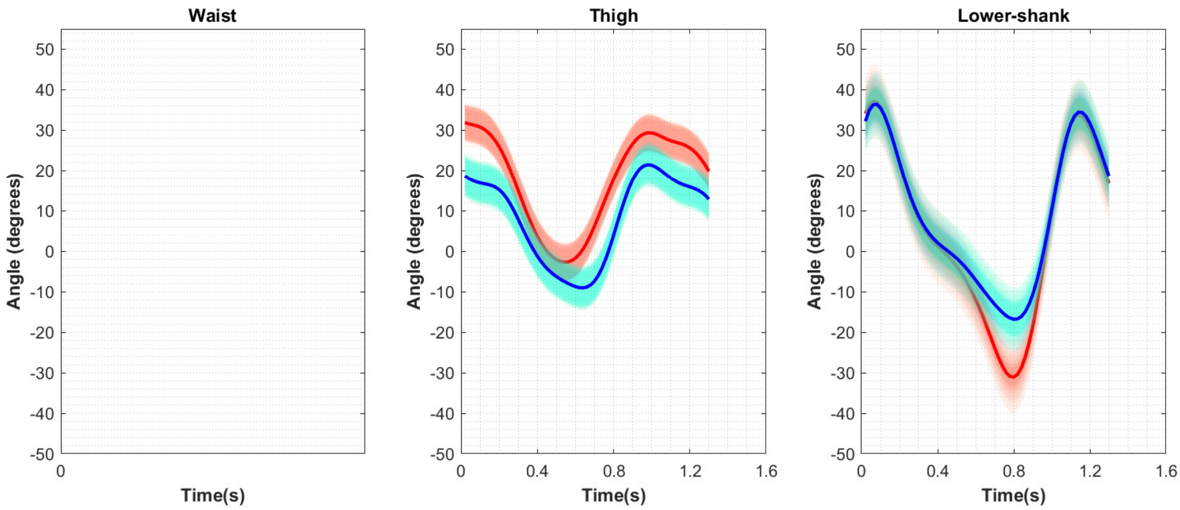

Figure C.6: Mean gait cycles for thigh and ankle sensors from ‘Participant 3- Day 2. Participant 3 did not wear a waist sensor pair. Body-mounted (red) and clothing-mounted (blue). Shaded areas on figures represent the standard deviation information.

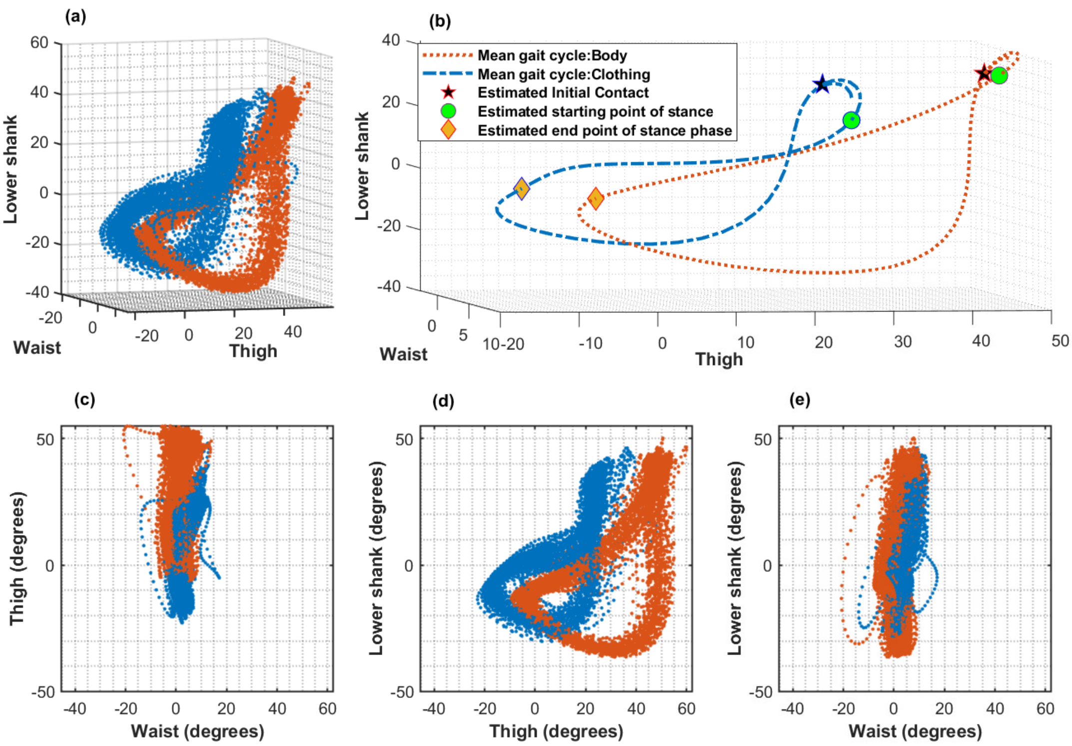

Figure C.7: As Participant 1's trousers were baggy at the thigh area, as expected the clothing data show a wider range of angles than that of the body-mounted thigh data. (a) 3D representation of body-mounted sensor angles (red dots) and clothing-mounted sensor angles (blue dots) for gait cycles for 'Participant 1- Day 1'. (b) Angle changes for the mean gait cycle for body-mounted (red) and clothing-mounted (blue) sensors for gait cycles shown in (a). 'Green o' s are the approximate starting points of stance phases (Initial contact) and 'yellow diamonds' s are the approximate end points of stance phases (Toe off). (c), (d) and (e) represent the angle data for 'thigh' vs 'waist', 'lower-shank' vs 'thigh' and 'lower-shank' vs 'waist' respectively.

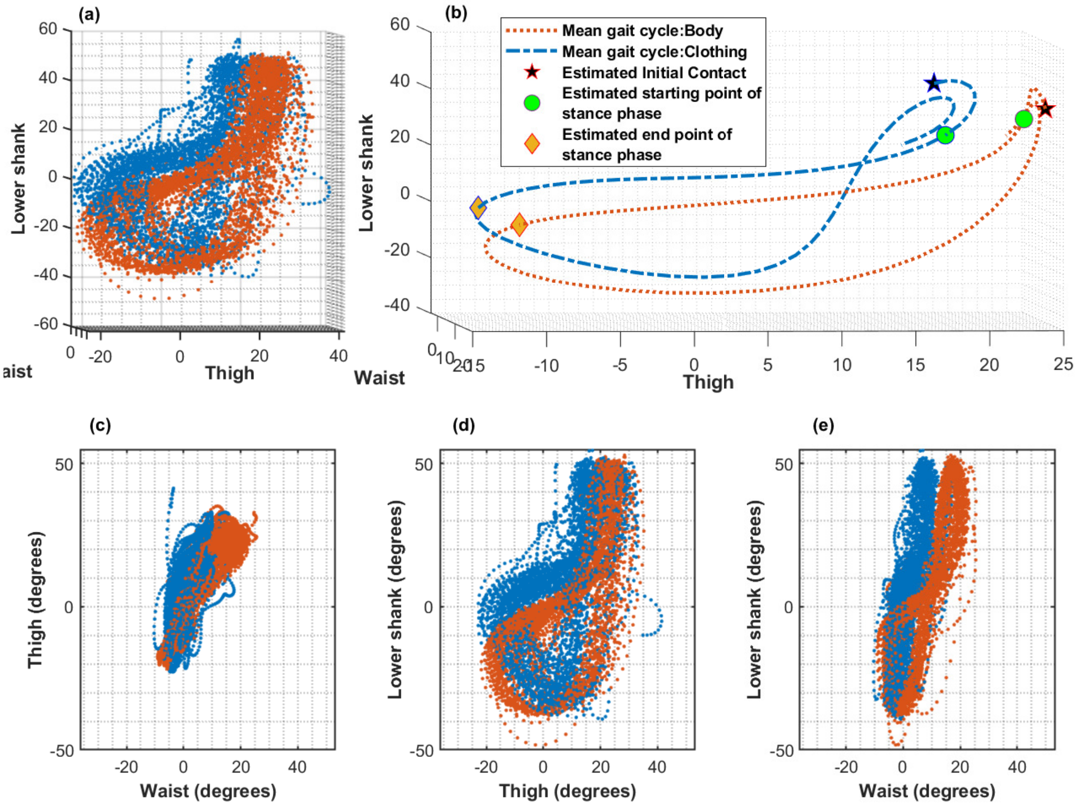

Figure C.8: (a) 3D representation of body-mounted sensor angles (red dots) and clothing-mounted sensor angles (blue dots) for gait cycles for 'Participant 1- Day 2'. (b) Angle changes for the mean gait cycle for body-mounted (red) and clothing-mounted (blue) sensors for gait cycles shown in (a). 'Green o' s are the approximate starting points of stance phases (Initial contact) and 'yellow diamonds' s are the approximate end points of stance phases (Toe off). (c), (d) and (e) represent the angle data for 'thigh' vs 'waist', 'lower-shank' vs 'thigh' and 'lower-shank' vs 'waist' respectively.

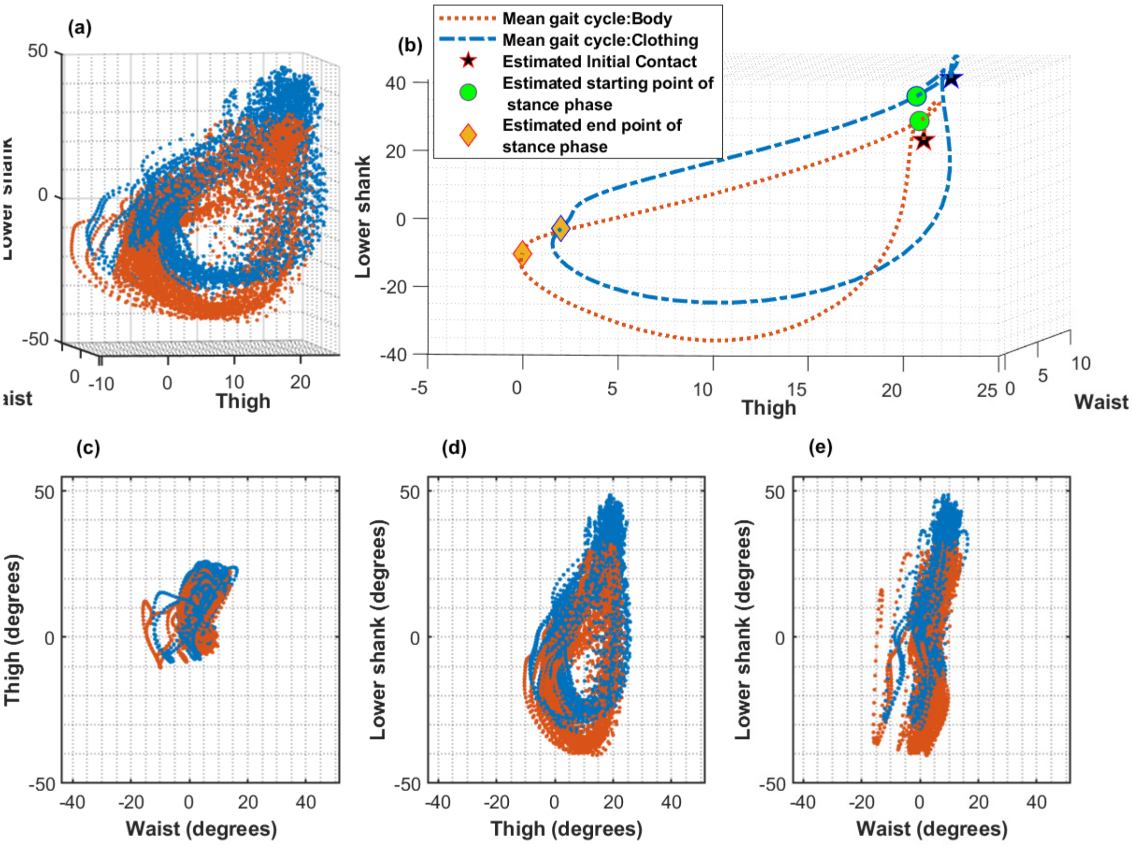

Figure C.9: (a) 3D representation of body-mounted sensor angles (red dots) and clothing-mounted sensor angles (blue dots) for gait cycles for 'Participant 2- Day 2'. (b) Angle changes for the mean gait cycle for body-mounted (red) and clothing-mounted (blue) sensors for gait cycles shown in (a). 'Green o' s are the approximate starting points of stance phases (Initial contact) and 'yellow diamonds' s are the approximate end points of stance phases (Toe off). (c), (d) and (e) represent the angle data for 'thigh' vs 'waist', 'lower-shank' vs 'thigh' and 'lower-shank' vs 'waist' respectively.

Appendix D

Appendices for Chapter 7

D.1 Activity wise summary reports for the participants

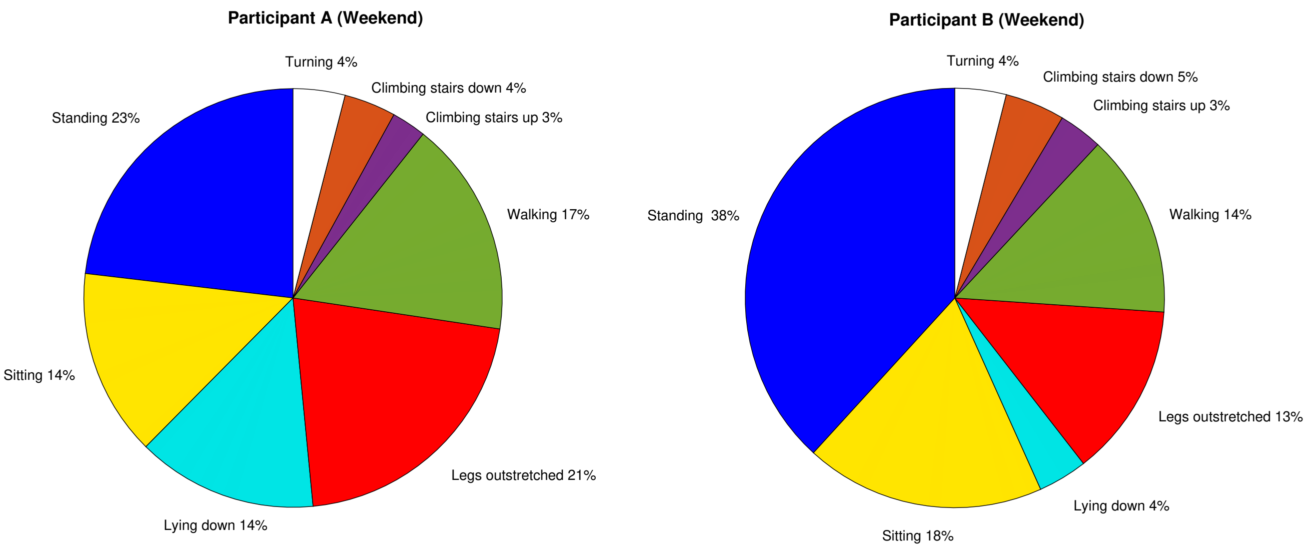

Figure D.1: Summary reports from each participant for a single day when they had the most dynamic activities.Participant A and B had a larger proportions of dynamic activities (28% and 26% respectively) on weekends compared to the other days.

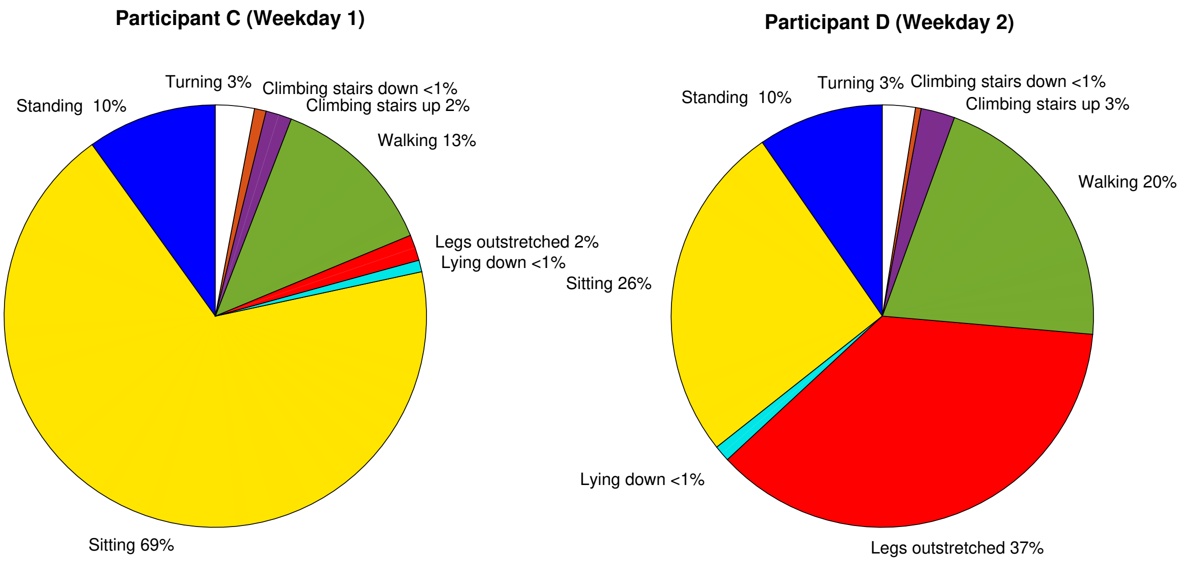

Figure D.2: Summary reports from each participant for a single day when they had the most dynamic activities. Participant C and D took part in the data collection only on weekdays and they had 18% and 26% of dynamic activities as the maximum values respectively.)

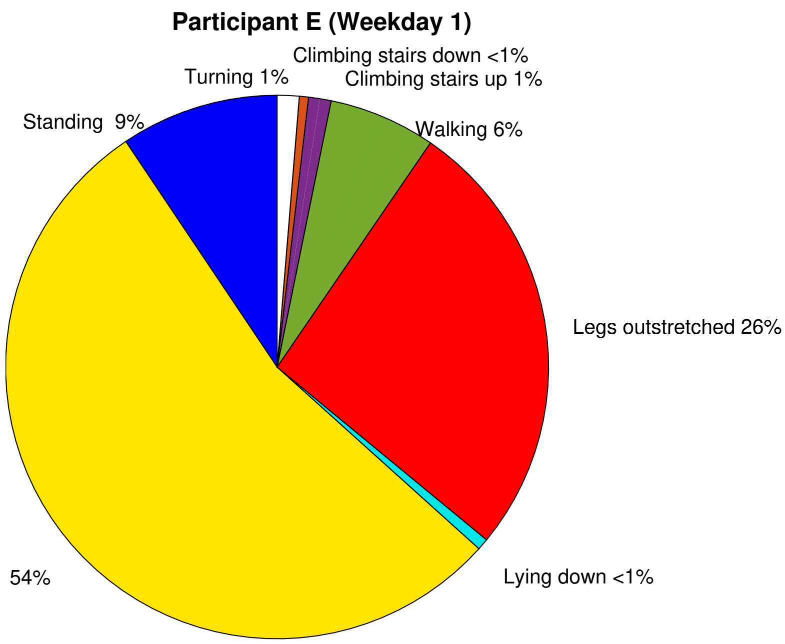

Figure D.3: Participant E took part in the data collection on a single day. The proportions of dynamic activities and static postures can be seen in this pie chart.