A Spherical Representation of Sensors and a Model Based Approach for Classification of Human Activities

Thesis submitted for the degree of Doctor of Philosophy

by

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Declaration

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

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Abstract

Physical inactivity is a leading risk factor in public health and inactive people are more vulnerable to having non-communicable diseases (NCDs), for example, autoimmune diseases, strokes, most heart diseases, diabetes, chronic kidney disease, and others. In addition, levels of physical activity may be an indicator of health problems in older adult individuals, a particular problem in many societies where there is a growing ratio of old adults age 65 and over. Identifying levels of physical activity may have a significant effect on fitness and reducing healthcare costs in the future. Thus, finding approaches for measuring the individuals' activities is an important need, in order to provide information about their quality of life and to examine their current health status.

This thesis explores the possibility of using low-cost wearable accelerometer based inertial sensors to determine activities during daily living. Two data sources were used for this investigation. The first was a locally collected data set recorded from individuals with Parkinson's disease in their own homes where they were asked to stand up from their favourite chair and then do different daily activities (*Bridge* data set). The second was a data set collected in a movement laboratory of the Fredrich-Alexander university and measures 19 participants doing daily activities (sit, stand, washing dishes, sweeping, walking, etc) in controlled conditions (*Benchmark* data set). Both studies used accelerometer based measurements as these are widely used in wearable and portable technologies such as smartphones, and are now finding use in health care applications.

Two areas of research are considered. In the first, accelerometer data were considered in relation to the surface of a sphere of radius $1g$ (i.e. magnitude of the acceleration due to earth gravitate). This research looked at sensor placement, window size and novel features based on the 'gravity sphere'. Decision Trees and Naïve Bayes classifiers were used as a baseline classifier on both data sets and k-Nearest Neighbour was used on the *Bench Mark* data set only. The classification results of a small set of activities of a single individual from first data set show that Naïve Bayes (NB) had a better overall accuracy rate than Decision Trees (DTs), where the results are 85.41% and 78.56% for both NB and DTs respectively.

The second area of work considered the possibility of using models of the dynamic system of the human movement as the basis for movement classification. Data from the accelerometers were used to evaluate two approaches that exploited the modelling capacity of a system identification algorithm. The two methods, which are called *Prediction Measuring* (PM) and *Model Matching* (MM), used the recursive least square method to identify a model for each class (activity). The *Benchmark* data set was used to verify the proposed methods. PM method achieved better classification accuracy comparing to MM method, with 71% and 59% respectively.

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List of Abbreviations

ADL	Activities of Daily Living
AgCl	Silver Chloride
ANN	Artificial Neural Network
BCG	Ballistocardiogram
BP	Blood Pressure
CART	Classification and Regression Tree
CHF	Congestive Heart Failures
CLOF	Class Local Outlier Factor
COPD	Chronic Obstructive Pulmonary Disease
CVD	Cardiovascular Disease
DD	Direct Density
DoF	Degrees of Freedom
DT	Decision Trees
ECG	Electrocardiogram
EP	Elastomeric Plethysmography
EPSRC	Engineering and Physical Sciences Research Council
EM	Expectation Maximisation
EMG	Electromyograph
GMM	Gaussian Mixture Model
IB	instance-based
ID3	Iterative Dichotomiser 3
IMU	Inertial Measurement Units
IP	Impedance plethysmography
KF	Kalman Filter

kNN	k-Nearst Neighbour
LAD	Latent Dirichlet Allocation
MEMS	Micro-Elector-Mechanical Systems
MM	Model Matching method
MMG	Mechanomyograph
NB	Naive Bayes
NCD	Non-communicable Disease
PM	Prediction Measuring method
PPG	Photoplethysmography
RIP	Respiratory Inductive Plethysmography
RLSF	Recursive Least Square with a Forgetting factor
SCG	Sonocardiograms
SPHERE	Sensor Platform for HEalthcare in a Residential Environment
SVM	Support Vector Machine

Chapter 1

Introduction

The need for inexpensive and high-quality health care is needed across the world [4] and across a range of conditions. Many methods and actions have been considered in an attempt to tackle this issue including new intelligent technologies [5]. For example, sensors and devices that are used to detect and normalise sleep apnea, accurate and painless diabetes monitoring, continuous temperature monitoring and fall detection for old adults and individuals with Parkinson's, stroke, frailty, obesity and cardiovascular diseases.

Recently, the ability to monitor the patient's status at home and enabling individuals to measure their well-being has acquired a high interest from multidisciplinary research groups [6]. Wearable technology that is used as healthcare monitoring systems can generate a substantial amount of data. The accurate analysis of this data is the key to gain the benefits of such a system. Machine learning and dynamical systems methods can be exploited to recognise patterns in data and provide useful information to individuals and healthcare providers.

This thesis develops new approaches for recognising human activities in relation to healthcare monitoring. The main focus is on extracting useful features from the sensor data in an efficient and adaptable way. A unique approach of this work is the use of system identification techniques to classify individual's activities.

Two concepts are explored, a Models Matching (MM) method and Predictions Measuring (PM) method. The approaches of human activities detection and classification using data of wearable sensor (primarily work has focused on sensors mounted on the person's lower-back/hip, wrist and ankle) are presented and the results are analysed and discussed. Two data sets were used for this purpose: Bridge data sets from the SPHERE project and, a Benchmark data set from Friedrich Alexander University in Germany.

1.1 Motivations

Finding methods to assess the individuals' activities of daily life and to carry out long-term monitor of their current health status is an urgent need in healthcare. This was recognised in a general area by Lord Kelvin who said "if you can not measure it, you can not improve it". There are two main factors that are relevant to long-term health monitoring. First, there is a rapidly increasing percentage of older adults around the world. In 2015, the United Nations reports for world population estimates that people aged 60 or over comprise a 12% of world population [7]. The reports show that the older adults' population has grown steadily by 3.26% per year. Second, inadequate physical activity is a leading risk factor in public health. It results in more than three million deaths each year, according to World Health Organisation 2013 [8]. That is because physically inactive people are more susceptible to chronic diseases. These factors are likely to cause a substantial impact on healthcare costs [9].

An automatic, accurate, real-time, reliable and easy to use and apply method to monitor individuals at risk in their home continuously could provide early detection of specific health threat factors, which would allow early and effective intervention [10]. New intelligent technologies might enable transparent detection and evaluation of the activities of daily life [11]. Recently, there has been a noticeable interest in health monitoring by using the latest advances in wearable technology. This technology could be used as a way of assessing health related activity and might enable older adults' people to live independently and in safety at home while reducing the cost of their healthcare.

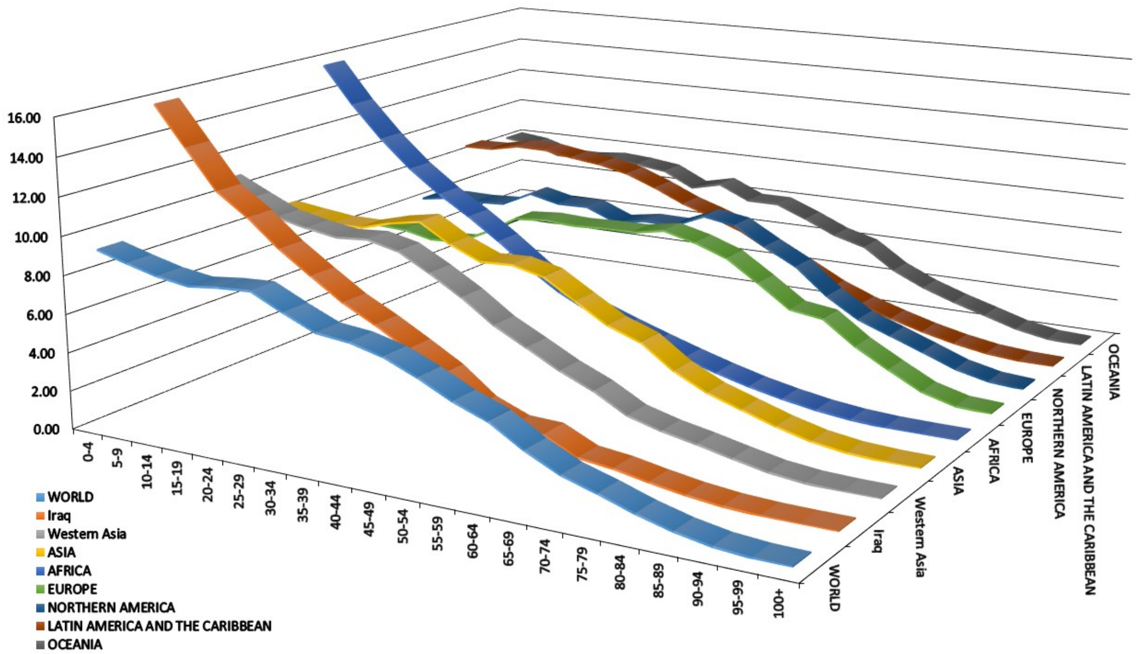
1.2 Medical health and ageing issues

Aging population and inactivity are the two important issues that put the healthcare system around the world under high pressure. This section presents these issues and referring to some statistics and future predictions.

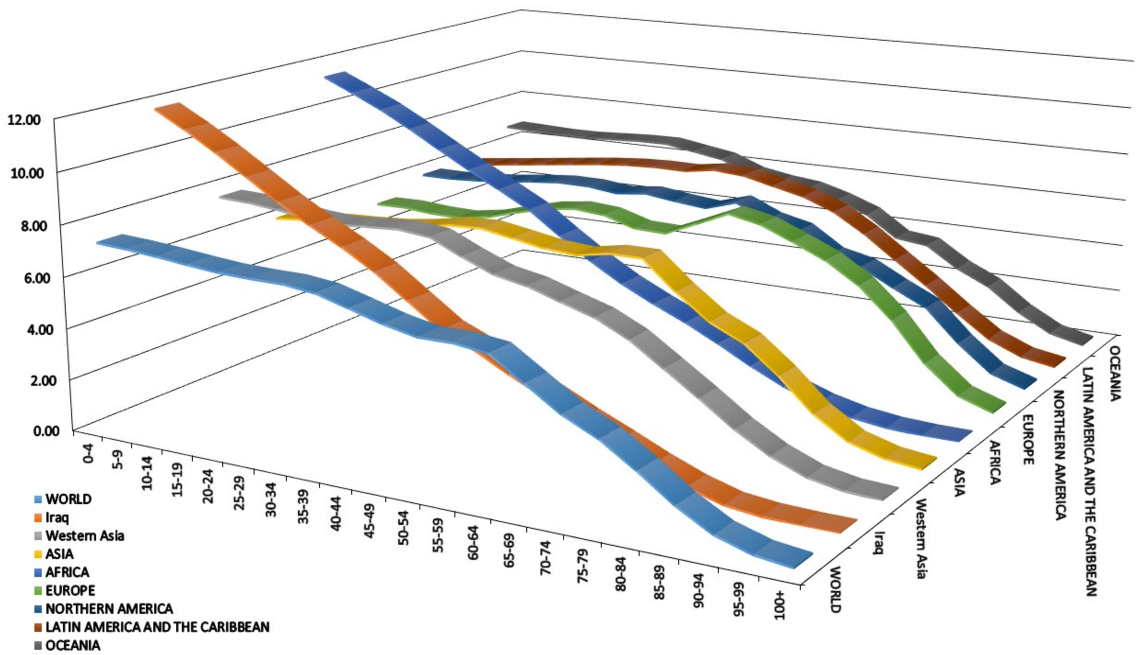
1.2.1 Population demographics

The fast increase of people aged over 60 globally is a significant issue that should be taken into consideration for public health. According to the United Nations report [7], there is a rise in the percentage of population over a specific age as a consequence of increasing life expectancy and decline of fertility throughout the world, which can be described as population ageing. For example, in 2015, 12% of the world population was comprised of people aged 60 or above with a growth rate of approximately 3% per year [7]. By 2030, the number of older people in the world will be about 1.4 billion, and by 2050 it will be 2.1 billion. This means that by 2050, roughly 25% of the population throughout the world (except Africa and some particular regions) will be aged 60 or above. Figure 1.1a shows the age world, major continents, region and Iraq population distribution in 2015, it is obvious that the percentage of people aged 60 or over is 12% of the world people, persons aged 15-59 are 62% and people aged 15 years and under are 26% [2]. Whereas, figure 1.1b

shows the expected age population distribution for the same places for 2050, where the high percentage of the older adult in this year can be seen [2]. The increasing number



(a) For year 2015



(b) For year 2050

Figure 1.1: Percentage of total population by broad age group, both sexes (per 100 total population) of the world, major continents, regions and Iraq. Figures created using United Nation data [2]

of older people means a rise in the number of people needing healthcare. For example, in the UK about one-third of older adults have at least one fall a year with a risk of having injury with potential for broken bones [12]. In addition, it can result in other problems, for example, the individual losing confidence and feeling like he/she has lost his/her independence.

1.2.2 Healthy ageing

In addition to the population ageing effects on healthcare, premature death and increasing rate of mortality may occur because of a number of reasons. According to a World Health Organisation (WHO) report for recommendations on physical activity for health, one of these reasons is physical inactivity which has been recognised as the fourth primary risk factor in general health [13]. The report shows that physical inactivity results in more than three million deaths each year, which means it is responsible for 6% of global mortality, following hypertension (13%), tobacco (9%) and high blood glucose (6%).

In addition, the report shows that the level of lack in physical activity is growing globally with dangerous consequences for the public health and for the spread of non-communicable diseases (NCDs), and with risk factors such as overweight, raised blood pressure and increased blood sugar. Another WHO report [14] shows that approximately half of the total worldwide disease burden was considered as NCDs. It estimates that the burden of roughly 30% of ischemic heart disease, 27% of diabetes and 25% of breast and colon cancer have been principally caused by physical inactivity. Furthermore, it gives an estimation that six out of every ten deaths are due to NCDs. The implications of physical inactivity affect all age groups, even children.

The overall conclusion, which confirmed by scientific evidence (WHO [13]) for the age group 5-17 years, points out that essential health benefits for children and youth could be provided by physical activity. Janssen [15] and Janssen et al. [16] suggested that approximately one hour of varied (moderate and vigorous) intensity physical activity per day could sustain healthy cardiorespiratory and metabolic risk profile for adolescents and children [17]. Sofi et al. [18], Cook et al. [19] and Warburton et al. [20] found a direct link between physical inactivity and metabolic health, including increasing of the risk of diabetes and metabolic syndrome. They recommended that for adults aged 18–64 years, spending of at least 150 minutes per week of moderate-intensity physical activity can improve cardiorespiratory fitness and reduce the risk of coronary heart disease (CHD), cardiovascular disease (CVD), stroke, and hypertension. Moreover, WHO states that for both age groups 18–64 and older aged 65 and above substantial health benefits gained by regular physical activity [13].

A similar health benefit is provided by moderate or vigorous intensity physical activity in both the above adult age groups [17]. Although additional health benefits are related to higher levels of physical activity, suggestions based on evidence that engaging in physical activity above 300 minutes per week results in a decreased marginal benefit of moderate intensity activity and increasing injuries risk for older adult's age group [13]. These factors cause a major impact on healthcare costs [9]. Thus, it is necessary to monitor and assess the physical activity of the individuals and find successful approaches for achieving that.

1.3 Objectives and challenges

The objective of the research conducted for this thesis is to accurately classify human activities of daily living (ADL) from data collected by residential healthcare wearable sensors, such as being developed by SPHERE, by reducing the complication of classification that depend on statistic operations and invest the dynamics in the human body postures and movements for this purpose. There are many research challenges in this area, including: individual privacy concerns, data storage and processing. This section highlights in more detail the research challenges and the corresponding research questions identified as the focus for this thesis.

- **Extract of useful features from the wearable sensors data.** A wearable sensor used for monitoring an individual's health status can generate a wealth of data. This data is complex, difficult to interpret and it can not be used directly by the person, carer or clinicians. Detecting, recognising and analysing of human activities from this sensor data would provide more useful information for these individuals. The knowledge obtained in real-time can be used to direct decision processes related to health and well-being.

  Existing works have demonstrated how to use a vast number of features extracted from wearable sensors to recognise human activities. This results in highly complex classification methods with high time and power consumption. To determine if it is possible to find significant features that can reduce the amount of data being processed and help the classification algorithms to achieve good classification accuracy is a current research challenge. That can be formulated as the first of three research questions:

  What are the key significant features in accelerometer sensor data that help to achieve high classification accuracy?

- **Invest the dynamic characteristics in the data.** Building a real-time system to recognise and analyse, thus can monitor the health status of the individuals, is an important need to indicate emergency situations such as falling and send appropriate help. Creating such a system can be achieved by using a method that considers human movements as a dynamical system. Exploiting the dynamics of human movement in the accelerometer sensor data have been poorly investigated previously. The challenge here is to find the viability of a time series approach to classifying human activities using accelerometer data. This challenge can be expressed as the second research question:

Could a time-series method be applied to classify human activities using accelerometer data?

- **Specify the best position of the sensor on the person body.** A health monitoring system that is based on wearable sensors needs to be attached in some way to the individual in order to monitor his/her current health status and to analyse a long term data to discover any changes in his/her health. Using many wearable sensors would be inconvenient which may make the system inapplicable. It is important to find if it is possible to use only one or a few sensors to recognise human activities accurately and to find the best location on the human body that enables the sensor(s) to collect significant data. This challenge can be expressed as:

  Can one wearable sensor recognise human activities in high accuracy and what is the best location for the sensor on the human body?

1.4 Contribution to knowledge

The contributions to knowledge for this thesis follow on from the research challenges identified and the formulation of associated research questions. These contributions are:

1. A model-based approach to movement classification. This thesis explored two concepts, the first was that of updating and matching a model of the movement to a database of previously recorded models. The second was to measure the predictive power of a database of previously stored models. Both approaches would allow models to both identify changes to movement patterns, and adapt to movement patterns.

2. A new approach to processing accelerometer data based on the idea that these

sensors measure both the person's movement and acceleration due to gravity. This allows features to be identified with respect to a 'gravity sphere' where postures become simply areas on the sphere and movements are considered with respect to the surface of the sphere.

1.5 Publication

A paper was published in Expert Update (2017), SGAI Workshop on data stream mining techniques and applications [21].

1.6 Thesis structure

An outline of the structure of this thesis is given here to facilitate navigation of the document.

Chapter 2 considers wearable sensors in healthcare. Two areas are considered: sensors to identify movement, and sensors to monitor physiological signals.

Chapter 3 outlines the machine learning and pattern classification techniques used in this thesis as well as some important techniques that could be used to extend this work.

Chapter 4 outlines the dynamical systems approach that forms the basis for the model matching (MM) and the prediction measuring (PM) methods concepts explored in this thesis.

Chapter 5 identifies the gravity sphere as a key concept in processing accelerometer data and shows some ways this approach can be used to identify movements and postures.

Chapter 6 identifies the concepts of the model matching (MM) and the prediction measuring (PM) methods for movement classification.

Chapter 7 gives conclusions and presents further possible areas for research.

Chapter 2

Monitoring of Human Activities for Healthcare Purposes

To live a healthily and actively life or at least to fulfil activities of daily living (ADL), a human needs to achieve certain physical activities in various scales. Thus, monitoring human physical activities is essential for assessing both patients and healthy individuals to determine their well-being needs. These ADL may include lying, sitting, standing, walking, stairs ascending, stairs descending, running, cycling, housekeeping, eating, chatting, watching, etc.. Every one of these activities could be taken in further detail to consider each aspect of daily life and professional activities. Furthermore, gaining knowledge about the ordinary tasks of a person is conjectured to be key to treat disorders in the human body. Some of the essential information could be provided from laboratory investigations such as video tape, clinical gait and audio-visual recordings. However, these examinations may miss a substantial amount of valuable data. Wearable sensors can be used as an alternative to clinical gait lab data collecting in both health and disease situations, and for different activities in various environmental conditions. A key benefit is the data collected in the context of activities for daily living. Thus, monitoring of human physiological activity might help patients with cardiovascular, neurological or pulmonary diseases, for example, cardiac insufficiency, high blood pressure, Parkinson's, epileptic seizures, asthma [22][23]. If detailed analysis of sensors worn in an everyday context can be done successfully, then abundant benefits could be gained for persons, family members and for the healthcare systems by using home-based recordings of human activity.

This chapter reviews the literature related to exploiting wearable sensors to detect ADL in a residential environment for healthcare purposes. The focus will be on the inertial measurement units (IMU) which are considered the most commonly used sensors to achieve this purpose [24][25]. Video cameras and ambient sensors used for human activity recognition are not considered in this review as they do not allow easy collection of ADL activities in the home context.

2.1 Wearable sensors

Although there are many types of sensors that are used to gather information for different purposes, over the last two decades there has been growing interest in studying and utilising sensors to collect data related to human health. Monitoring of human activities and physiological parameters has to be achieved with sufficient accuracy and through a sustained time period so that important events such as falls, stumbles, near falls or unusual gait conditions can be recorded. Rapid development in microelectronics, micromechanics, and other technologies have yielded non-invasive sensors providing fast and accurate measurements and requiring lower power consumption. These sensors, which consider the primary element of monitoring systems, help in satisfying the above necessities.

Various types of wearable sensors can be used for measuring human activities. These sensors will be considered in three categories: bio-metric sensors, motion sensors and environmental sensors. In the context of this thesis, the following taxonomy will be assumed. Bio-metric sensors are used to measure physiological signals such as heart rate, blood pressure, blood oximetry, respiration, galvanic skin response, heat flux, hydration level, blood sugar, perspiration, or muscle activation (e.g. using mechanomyography (MMG) or electromyography (EMG)). Motion sensors are used to capture individual movements, in particular inertial sensors including gyroscopes, accelerometers, and magnetometers can capture a set of parameters related to movements. Inertial measurement units (IMUs) can be used for biomechanical modelling and can be made for 9 degrees of freedom (DoF) tracking by merging a tri-axial accelerometer, gyroscope, and magnetometer. Finally wearable environmental sensors are assumed to measure parameters such as temperature, light, or pressure changes.

In order to use wearable sensors in a practical way, it should meet a number of important principles. They should be reliable, easy to use, non-invasive and provide accurate and relevant feedback to the user in an appropriate and easy-access format [26]. The sensors can be worn as accessories, clipped or combined into shoes or clothing, and/or attached directly to the person's skin using a clip, belt, strap or adhesive material. Significant advances have been achieved in sensors technology in the last ten years such as micro-elector-mechanical systems (MEMS) and physiological sensors [27]. Low power wireless communication feature enables this new technology to be used as wearable devices without a need to consider the restrictions of wires, recharging and data storage.

2.1.1 Bio-metric sensors

The healthcare literature reports that in order to determine the clinical disorder, various sets of important vital signs should be monitored. The five vital signs that are the most significant to be assessed are heart rate, blood pressure, respiration rate, blood oxygen saturation and body temperature. Continuous monitoring for these signs could be made to evaluate individuals' health especially the individuals with chronic health-related conditions (e.g. Parkinson's disease, strokes, COPD (Chronic Obstructive Pulmonary Disease), frailty, etc.).

Additional vital signs can be added to the previous one, such as the glucose level, urine output, pain, level of consciousness, capnography (to assess ventilation), and stroke volume (to assess heart performance). According to Ahrens [28] and Coventry [29], Changes in patient's physiology could be accurately recognised by combining all of the previous vital signs.

Different types of wearable sensors are used to monitor these vital signs. Integral analysis of all these data streams could be effective for better management of the disease conditions. Each one of these wearables could be used to gather data of one sign or a number of signs as discussed in the following subsections.

2.1.1.1 Electrocardiogram (ECG)

The ECG is important to analyse the heartbeat rhythm and to predict acute myocardial infarction and coronary events. The ECG's waveform analysis takes a key role in the identifying of cardiovascular diseases (CVD), including: atrial fibrillation, angina, arrhythmia, atherosclerosis, congestive heart failures (CHF), coronary artery disease, heart attack, bradycardia and tachycardia [30, 31].

Wearable devices that used for medical purposes and ECG monitoring have an advantage which is the improvement of early detection of atrial fibrillation. That's because of continuous monitoring for a long period compared with Holter (Holter monitor is a device used to track heart rhythm by attaching it to the patient chest. For example it might be connected for one day, two days, or a week on a yearly basis).

Currently, Ag/AgCl electrodes are commonly used to transform the heart ionic current to electron current in wires. They characterized by reliability, compacting and low cost. However, because of their wet component and adhesive attributes, skin irritation can be caused. In addition, the contact between the electrode and the skin may be reduced during long periods of monitoring as a result of gel dryness. Holters are generally used for long monitoring, their main drawback is the interruption of patient daily life routine. Dry electrodes and fabric embedded electronics using different materials have been developed to work around this problem [32, 30]. Human sweat is used by these electrodes to sustain contact with the skin rather than conductive gel. Although this type of electrodes does not cause skin irritation, they are not consider as clinically acceptable for now due to their not adhesive property which affects, with motion, the accuracy of the measurements. Because motion can change the external pressure which results in affecting the electrode contact with the skin.

A dry, flexible and stretchable sensors has been developed by Luo et al. [33] that overcome skin irritation and to decrease the noise caused by body motion, which still needs to be used inside the medical environment as it is attached to the skin.

A non-contact capacitive electrode is another type of ECG sensors. Aleksandrowicz and Leonhardt in [34] reported that these devices have the ability to collect the ECG signals without contacting the skin directly, but they are affected by movement artefacts, compared to traditional electrodes.

2.1.1.2 Heart rate

Heart rate is a typical vital sign and it has become a fundamental measuring in human healthcare, fitness and sports activities. By monitoring this sign, important information about human physiologic status can be provided. Simply, ECG and photoplethysmography (PPG) signals can be used to extract this vital signal [35].

Both of these physiological signals contain comparable heart rate information, although they belong to different physiological sources and have dissimilar morphologic information. Simple, but not necessary reliable, PPG have become more common with the introduction of wearable devices such as the Apple Watch.

Ballistocardiogram (BCG) [36] or inertial sensors [37] are other methods to monitor heart rate. However, the heart rate extracted using these ways do not have functional measurement comparing with ECG and PPG.

As a simple indicator of the cardiovascular system status, the analysis of heart rate variability is gaining vast attention. In addition, it is an indicator of the individual psychophysiological status as it may be used to detect fatigue, stress or anxiety measurements [28, 38].

2.1.1.3 Blood pressure (BP)

It is a significant cardiopulmonary parameter, which points out the pressure applied by blood against the arterial wall. Information about the blood flow and cellular oxygen delivery can be provided indirectly by BP. Cardiovascular diseases prediction can be improved by measuring the blood pressure several times a day using ambulatory BP monitoring, especially for patients who have high blood pressure which considers the most threats to the global burden of diseases [29, 39].

Using the traditional methods for measuring blood pressure continuously could lead to undesirable side effects, such as skin irritation, sleep disruption and stress level increasing. New technologies have been developed to solve this issue [32]. Recently, an experimental watch-type prototype has been proposed by Woo et al. [40] as a wearable device giving a real-time monitoring blood pressure continuously using a pressure sensor near the radial artery, providing a precise measurement on a smart-phone.

In general, direct blood pressure measurement is unlikely to be feasible in practical wearable sensors. However, it is likely that blood pressure can be modelled by combining data streams such as ECG, respiration and inertial data.

2.1.1.4 Respiration rate

Respiration rate is considered an essential physiological parameter in a patient's monitoring. Assessing of respiration rate provides accurate and key health information in a number of cases as in acidosis [29]. It is very important to use ambulatory monitoring of respiration rate to detect respiratory diseases symptoms, i.e sleep apnea, asthma and chronic obstructive pulmonary diseases; and in improving the administration of the treatment. This continuous monitoring is especially important for children who have a pulmonary disease [29, 35]. A better respiration performance can be achieved particularly for the athletes by analysing their respiration rate data [29, 35, 38].

Normally, This vital sign is estimated from the acquired respiratory waveform that reflects the chest volume difference during the breathing. Currently, there are three main methods to obtain the respiration rate: elastomeric plethysmography (EP), impedance plethysmography (IP) and respiratory inductive plethysmography (RIP). Using an elastic belt, the EP method transforms the current difference of piezoelectric sensors in to voltage. A prototype garment was developed by Guo et al. [41] to measure accurately the volume change of chest and abdominal using a piezoresistive fabric sensor. The IP technique is based on impedance changes of the chest surface because of expansion and contraction of the breathing process. A uniform vest has been developed to be used for soldiers, using this technology [42]. The RIP method depends on a magnetic field generated by a wire loop with a suitable current. An opposing proportional current will be created in a second loop due to the chest volume difference changing the area enclosed by the loop [43].

In addition to these three main technologies, there is a number of techniques to calculate the respiratory waveform, such as using accelerometers [44], optical fibres [45], polymer-based transducer sensors [46], got from the ECG signal [47], derived from pulse oximetry [48], etc. A review has been made by Al-Khalidi [49] about the technique used to assess respiration rate. This review referred to several methods that are not applicable to be exploited in wearable devices, for example using acoustic methods or infrared cameras. Recently, a polymer called Polypower is using to gather the respiration rate. When this polymer stretched in one direction it will change its electrical attenuation. Tognarelli et al. [50] are using this method to acquire the chest volume difference, presenting the potentiality of dielectric active polymer in this area [50, 51].

2.1.2 Inertial measurement units (IMU)

Inertial sensors sense the object's linear and angular acceleration, possibly linking these to the earth's magnetic field. Most of them sense the acceleration in three orthogonal axes. Therefore, they can be exploited in measuring complicated applications with significant accuracy [52]. Commonly available inertial sensors types now include gyroscopes, accelerometers and magnetometers, which used to measure the angular velocity, acceleration and magnetic fields, respectively [19]. Each of these measurements is up to three orthogonal axes. By merging a tri-axial gyroscope, accelerometer, and magnetometer inertial measurement units (IMUs) can be made for 9 degrees of freedom (DoF) tracking. By this, they can be used to measure the full kinematic mobility. However, these measurements are subject to noise and often involve an offset that complicates the process of integrating the acceleration measurements to estimate position and angle.

Generally, an accelerometer is a device which senses differences in acceleration. Figure 2.1 depicts the three major elements of a simple accelerometer. An accelerometer sensing element is a mass, made of some sort, which affected in response to an acceleration vector. A spring is holding the mass in its resting position and a displacement transducer is used to measure the mass movement amount according to an applied acceleration.

Figure 2.2 depicts a diagram which illustrates the mechanism of sensing differences in acceleration in MEMS accelerometers. In this figure, the sensing element (mass), which is made of a deposited polysilicon layer, is simply a backbone that has fingers extended from it and is suspended by elastics at both sides. The elastics ends are attached to underlying silicon stanchions which act as the anchor points. Fixed plates (electrodes)

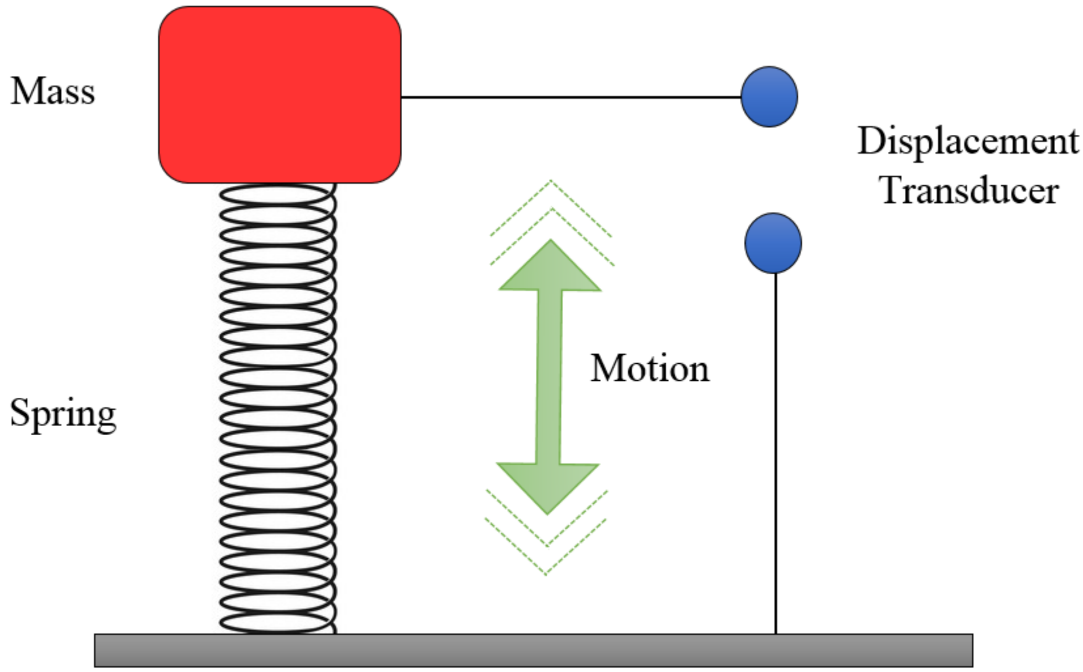


Figure 2.1: A diagram of a basic components of a simple accelerometer.

are attached to the anchor points as well, which act as the displacement transducer. The elastics provide the spring function that showed for the simple accelerometer of figure 2.1.

In these sensors, the scale of mechanical elements was reduced to microelectronic scale by utilizing microelectronic processing techniques [53]. Therefore, a single chip of MEMS can contain both the mechanical sensor components and their associated signal processing electronics. These sensors comprise one fixed plate and one mobile plate. The fixed plates remain stationary within the device, while the mobile plates connected with flexible structure which hold a mass between them. When the mass experiences an acceleration, it will respond with a force according to Newton's third law (f=ma). This force is exerted on the springs and the mass moves proportion ally to the acceleration. This will result in a difference in the distance between the mass movable plate and the external fixed plates. These external plates act like a capacitor.

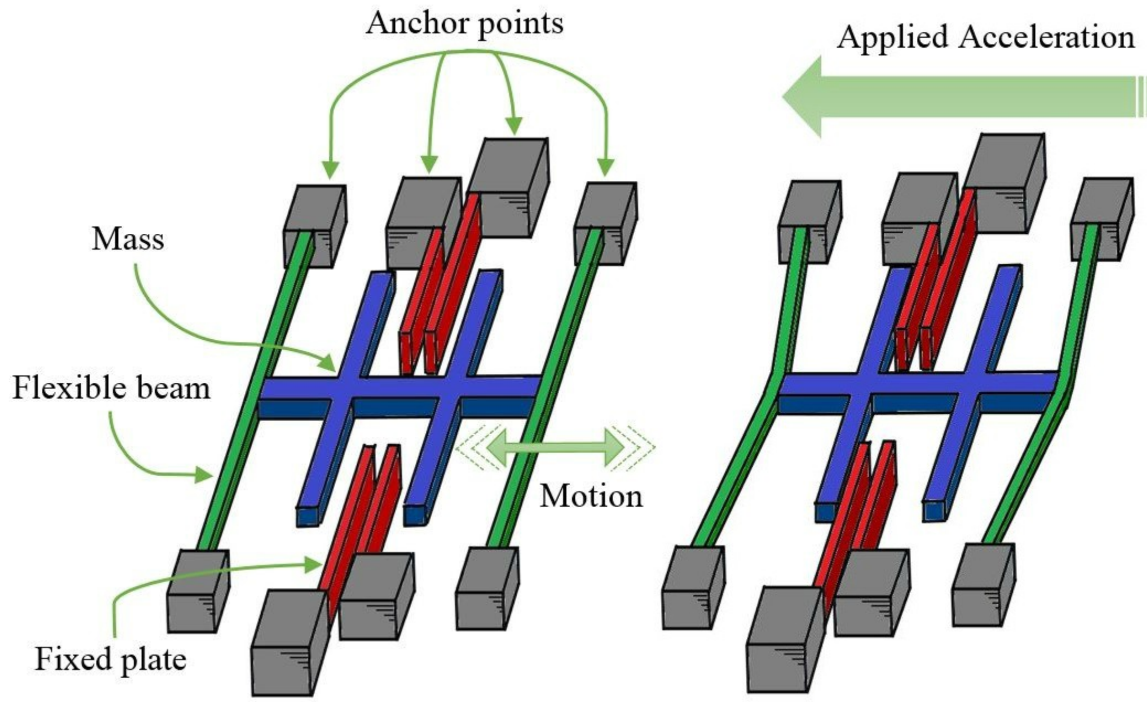


Figure 2.2: A diagram of a MEMS accelerometer showing mass and flexible beams as its basic components.

If these plates are driven with an alternating voltage, a change in capacitance proportional to the plate separation can be measured and will be proportional to the difference in the distance between them. This capacitance change is measured by electronic circuitry. The output of this circuitry will be the acceleration measurement.

IMUs have been exploited for applications in a substantial number of domains, for example automotive [53], aerospace [54] and crash testing [55]. However, as the IMUs are to be employed in recognition and analysis of ADL and human activity recognition (HAR), section 2.2 will be focused on the use of inertial sensors for human monitoring.

2.1.3 Environmental sensors

Environmental sensors are used to sense the subject surroundings which related significantly to human body monitoring in several aspects. The commonly used sensors are light, temperature, humidity, sound, and air pollutants.

The human body is subjected to the influence of its outdoor environment during daily activities, sport or rehabilitation exercises. This influence should be monitored with environmental sensors to examine the ambience characteristics that the individual is subjected to, for example, the temperature and the humidity are essential to assess dehydration [56]. In an indoor environment, it is easy to estimate the individual's metabolic rate using environmental sensors because of the non-contribution of exterior influences. Jin et al. [57] have shown that a number of daily indoor activities could be recognised by measuring temperature, light and humidity patterns.

Furthermore, these sensors can be used to evaluate the quality and quantity of sleep by collecting temperature, sound and light data. For instance, by joining the inertial sensor with a sound sensor it is possible to assess sleep disorders especially for people who live near airports [58].

Worn environmental sensors are included here for completeness but have yet to be seen widely in healthcare or consumer applications. They are more common in hazardous industrial applications such as monitoring the radiation dosage of people working in the nuclear industries.

2.2 Healthcare applications using inertial sensors

Inertial sensing can be utilised in the recognition of human postures, gait and activities such as sitting, standing, walking, running, etc. This type of sensing is exploited in many applications. The literature in the field of inertial sensors applications is vast and it is not appropriate to include everything here. The following subsection present the common inertial sensor applications in the literature.

2.2.1 Activity recognition

Activity recognition for healthcare using wearable inertial sensors has substantial applications. For example, a method for detection of behavioural symptoms of autism was proposed by Minnen et al. [59]. High-level behaviours were detected from low-level activities by using three microphones and two accelerometers placed on the participant's body and recording the data by an on-body data-logging computer. The researchers used simple classification routines to good effect. Although three microphones, two sensors and data logging computer were worn by a person with behavioural syndromes, the hardware suitability for the application was not discussed.

Niall Twomey [60] achieved promising results in recognising between allergic and non-allergic individuals using a wearable accelerometer to record the human movements and ECG to record heart rate variability. He used a GMM classifier to recognise between the two classes. Such an accurate and non-invasive method is very useful in comparison with the traditional allergy diagnosis in a clinical environment that required tests such as blood, skin or challenge test.

An approach presented by Staudenmayer et al. [61] includes data of 48 participants conducted light, moderate and intense exercise for 10 minutes each exercise. They achieved very good classification results. In addition, they illustrated how to estimate the energy expenditure by accelerometer analysis. When compared their acquired results to the ground truth showed the results were competitive with other researchers, such as Freedson et al. [62], Swartz et al. [63] and Crouter et al. [64]. The obtained results included activities required a high level of energy, e.g basketball and racquetball. However, a test involving such activities should not exceed 20 minutes in length, because of the metabolic response of individuals after this period could be unreliable [65]. This is because, after the body performs intense or lengthy physical exertion, various factors will affect the metabolic response which is experienced. Thus, it is possible that

Staudenmayer et al. [61] results might have been corrupted by this attribute, although these results were accurate.

In the last decade with integration of the accelerometers in the smartphone, activities assessments have become accessible for smartphone users. Energy expenditure estimation is one of the research areas that investigated through accelerometer analysis. An individual's daily energy expenditure can be estimated using the smartphone accelerometer data alone. In fact, an anti-obesity applications were associated with social networking websites, where daily achievements can be posted as a way to encourage exercise [66]. There is great interest in research in activity-based intervention monitoring to reduce obesity [67, 68, 69].

A comprehensive review of approaches for recognising ADL using only the mobile phone with the integrated inertial sensor was presented by Pires et al. [70]. They show a summary of the advantages and disadvantages of various techniques. Their conclusion was the choice of the best approach depend on a number of factors specific to a particular application. Bao and Intille [71] used five bi-axial accelerometers to collect data from 20 volunteers performing 20 activities. The set of activities were selected to simulate ADL at different levels of intensity, which included reading, brushing teeth, walking and folding laundry. The sampling rate of the accelerometers was 76.25 Hz. A semi-naturalistic protocol and a controlled collection procedure were both used to in the data collection. The features extracted from the accelerometer data were mean, energy, entropy and correlation.

To achieve activities classification, Bao and Intille used Naive Bayes, C4.5 decision trees, decision tables, nearest neighbour classifiers. They found that a decision tree classifier achieved the higher classification accuracy with an overall rate of 84%. The results also showed that a high classification accuracy was achieved with data collected under the semi-naturalistic protocol comparing with previous researches done on a data collected in a controlled environment.

Using multiple sensors to analyse human activities is not realistic for the long term monitoring as the user could find them obtrusive. A single waist-worn triaxial accelerometer sensor with sampling rate 50 Hz was used by Wang et al. [72]. They used a hidden Markov model (HMM) to classify data of 13 healthy participants (aged 26 to 50 years) who performed the following set of activities: walking, standing, sitting down, falling, jumping and running. The HMM classifier was trained on a subset of the collected data. Various parameters were investigated and validated on the data not used for training. The highest classification accuracy of 94.8% was achieved with 7 hidden states and 3 mixture components. In addition, the authors found that most misclassified activities were sitting and falling which might be because sitting is similar to controlled falling from the point of view accelerometer signal.

2.3 Chapter summary

This chapter has reviewed the literature related to the use of wearable sensors to detect ADL in a residential environment for healthcare purposes. The advantages of wearable sensors in collecting relevant data about human health status that could help to treat human illness were discussed in comparison to clinical laboratory methods. Three categories of wearable sensors were described. These were categorised according to the type of data they collect. These categories are (i) bio-metric sensors, (ii) inertial sensors including accelerometers and (iii) environmental sensors. The types, advantages and disadvantages of each one of these three categories were discussed.

As this work used the inertial sensors, these were the main focus of this chapter. The basic structure and mechanism of these sensors were described along with the domains that they find typical applications. The investment of the IMU in human activity recognition was discussed and the literature that used these sensors were reviewed including algorithms and data sets.

A key issue with previous work in this area is the reliance on arbitrary features for classification. This thesis explores a model-based approach to decision making for healthcare moment analysis as this allows classification decisions to be understood and may enable other information to be derived from the classification process.

Chapter 3

Literature on Machine Learning and Classification

A person's ability to achieve ADL and his/her physical activity levels are the main indicators of his/her health and well-being [73, 74]. By monitoring these indicators, older adults and people with chronic diseases can live independently in their home for longer [75]. In addition, it is important to monitor human activities in a residential environment continuously for early detection of disorders and any health issue [73, 76]. Many machine learning algorithms have been exploited to classify human activities. This chapter reviews classification algorithms applied to the data that can be collected from wearable sensors using healthcare monitoring systems in a residential environment.

3.1 Features based classification methods

Generally, features based classification methods can be distinguished into two main types: supervised and unsupervised algorithms. The main differences between them are the approach used to deal with data and the nature of the data itself. This section describes some of the widely used algorithms of both types.

3.1.1 Supervised classification

This type of classification needs previously classified data samples in order to train the classifier and subsequently classify unknown data. This section provide a brief explanation of some of the wide use supervised classification algorithms.

3.1.1.1 Decision Trees (DT)

Decision Trees or rule-based algorithms is a widely used classification method. A model can be constructed by this method from a data set in the form of a decision tree or a set of decision rules. The root is the starting point that is split into decision nodes. By repeatedly splitting according to the data values, decision nodes are refining the class prediction with each level of them. Leaf nodes are the terminals of the tree which represent the predicted class of unknown data [77]. DT algorithms are available to automatically generation classification rules based on the data, such as ID3 and C4.5, although it can be created manually by experientially defining rules. Random tree, random forest, CART and J48 are examples of other available DT algorithms. Examples of the use of DT for human activity recognition include [78, 79, 80, 81, 82, 83, 84, 85].

3.1.1.2 Naïve Bayes (NB)

Based on Bayes theorem, Bayesian inference methods relate the prior probability of the hypothesis, the posterior probability of the hypothesis happening given the features and the probability of the features given the hypothesis (the likelihood). This approach combines prior and conditional probabilities to determine the probability of alternative classifications. It is “a method of classification that uses mathematical probability theory to find the most likely classification for an unseen instance” [86]. NB can perform well regardless of the assumption of its dealing with the data features independently, which often considered as a drawback. NB classifier is a common method for recognising activity from sensor data [27]. The Bayesian classification was used by Atallah et al. [87] for activity recognition from a data of an ear-worn accelerometer sensor.

3.1.1.3 k-Nearest Neighbour (kNN)

It is one of the simplest algorithms used for classification. This method classifies unlabelled data instance according to the classification of the closest data to it. This is achieved by measuring the distance between the unlabelled instance and the nearest labelled instance or instances (i.e. training data) using a distance measure, e.g the Euclidean or the Manhattan distance measurements, where k is the number of training instance that must be considered. This results in assigning the unlabelled instance a label of its nearest neighbour (i.e. instance). Although it is a simple algorithm, it has been used and reported widely in literature [88, 80, 81, 89, 90, 91, 92, 93]. For example, a comparison was made by Bicocchi et al. [91] between kNN and a number of instance-based learning algorithms, these are IB1, IB3, IB6, DD3, DD6, CLOF3 and CLOF6, using k=1 and a real-life activity set. They show that kNN achieved a classification precision of about 75%.

3.1.1.4 Support Vector Machine (SVM)

SVM is one of the classification algorithms that have been widely used for human activity classification [88, 78, 93, 83, 94]. It can be exploited for both linear and non-linear classification applications. SVM is a binary classification method that finds a separation between two classes.

However, SVM can be used as a classifier for a multiclass problem by performing multiple binary classifications using the one-versus-all strategy [95]. Using a kernel function, SVM can achieve mapping for feature vectors, which belong to not linearly separable sensor data, into a higher-dimensional feature space where a hyper-plane is used to separate them [27].

For example, polynomial, Gaussian, radius basis function or hyperbolic tangent function are common kernels that have been used. Liu et al. [88] in their study to specify the best configuration for the sensor for activities recognition, they found that SVM outperforms kNN and Naïve Bayes classifiers with 75% accuracy using a single accelerometer attached to the hip and 88% using two accelerometers worn on hip and wrist.

3.1.1.5 Artificial Neural Network (ANN) and deep learning

An ANN is a computational model inspired by information processing in biological systems which used to describe functions comprising of a network of simple computing elements or nodes [96]. An ANN structure consists of multiple layers of nodes connected by weighted links. To achieve the computation of the network output, the ANN inputs are propagated forward through its layers. This can be achieved by: first, for each node, finding the sum of the weights multiplied by the input value of all inputs. Then, using an activation function (e.g. sigmoid function), the node output is calculated. The internal linking weights are adjusted using methods such as back-propagation to train the network. The concept of these methods is to reduce the error amount between the actual network's output and the target output [97].

ANN have been used widely for human activity classification and recognition, some instance includes [79, 93, 98, 99]. Altun et al. [93], Parkka et al. [79] and Roy et al. [98] carried out comparative studies between the ANN performance and other algorithms. An activity recognition method achieved by Yang et al. [99] consists of two phases. The first phase implements the classification of activities to either static or dynamic activities and the second phase implements further detailed activity recognition.

3.1.1.6 Fuzzy logic

Fuzzy logic or fuzzy set theory is multi-valued logic with special properties which aims via a graded method to modelling of the ambiguity phenomenon and some parts of the meaning of natural language. [100]. Fuzzy logic defines input data in terms of probability, which is the probability the input data describes some attributes [101]. This method can be used for human activity recognition using data from both ambient and wearable sensors [102, 103]. Three main steps have been described by Medjahed et al. [103] for the implementation of fuzzy logic. The first step is to perform the fuzzification which implies the conversion of the data into fuzzy sets. Then the implementation of a fuzzy inference system that contains fuzzy rules in the form of IF-THEN rule and fuzzy set operators (including the complement, union and intersection) [101]. The last step is to apply the defuzzification that converts fuzzy variables to real values.

3.1.2 Unsupervised classification

This type of classification is known as self-organisation. It does not require previously labelled data samples. It looks at the structures in the data and builds models using e.g. probability densities of given inputs. This section presents a brief description of some of the commonly used unsupervised classification methods.

3.1.2.1 *k*-Means clustering

k-means is a popular clustering algorithm uses an iterative based-distance method to update the parameters of each cluster. The object of this approach is to classify the data according to the distance of a data point to the mean centroid of every cluster. The training of the classifier starts by identifying k centroids, one for each cluster. These can be selected randomly or by identifying the initial centroid according to all of the training data and the follow centroids using the furthest data points from the initial centroid [101]. This approach may achieve better results by picking the k initial centroids fairly far apart [104].

The distance of the centroids from the data points is minimised by using an iterative process. The data points are assigned to the nearest centroid for each one of them. Then the centroids are recalculated based on the clusters that are created. This process is repeated until some convergence criterion have been met. After this, classification data is assigned to the nearest centroid. k-means clustering was used by Chassemzadih et al. [90] to define movement transcripts, which formed by representing each motion as a sequence of basic building blocks called primitives, that used for action recognition. Machado et al. [105] invested k-means clustering to the human activity recognition problem using accelerometry successfully predicting activities with an accuracy of 99% and 89% for the person dependent and independent cases respectively.

3.1.2.2 Gaussian Mixture Model (GMM)

GMM can be considered as a parametric classification method which modelling the probability distribution of continuous measurements or features. GMM is comprised of a weighted sum of Gaussian distributions which could be trained using example data by an algorithm such as expectation maximisation (EM) [82, 106].
For each class, a GMM should be trained. Then, the determination of the new data class can be done by finding the GMM that have the highest likelihood of producing the data. Allen et al. [82] used GMM to monitor old adults by recognising their postures and movements using a single accelerometer data, comparing it to a rule-based Heuristic system performance. Wang et al. [106] used GMM for the classification of five different human gait patterns, achieved an overall classification error rate of 4.88%

3.1.2.3 Topic models

Topic models are a machine learning technique whose original purpose is to help the understanding of large corpora of text. By using a generative statistical model known as latent Dirichlet allocation (LDA), Topic models are used to discover hidden thematic patterns in a data set. They have been used in the discovery of routine behaviours, e.g. lunch, from activities such as queuing and eating, as showed by Huynh et al. [107] and White [108]. The stability of topic models' performance for the discovery of daily routine was further investigated by Seiter et al. [109]. They achieved that by varying the attributes (the duration of routines, amount of data and specificity of routines) of simulated data sets according to the original data collected by Huynh et al. and identifying optimal values of data set properties desired to obtain robust performance.

3.2 Sequence classification methods

In general, an ordered list of events is called a sequence. An event can be represented as a numerical value, a symbolic value, a vector of values or a complex data type. One of the sequence data types is time series which is an order of real values sequenced according to a timestamp [110].

Sequence classification has been used in a wide range of application such as detection and recognition, health informatics, information retrieval, genomic analysis, and finance.

This section locks at less obvious methods for classification and presents a brief explanation of some of these methods.

3.2.1 Kalman Filter (KF)

KF is a widely used statistical state estimation algorithm. A system state estimates can be determined based on a recursively applied estimation and update algorithm, and the current system state is based on the system state at the previous time interval. One of the main advantages of KF is that it requires Little computational power [111]. The common usage of KF is for real-time tracking applications [96, 111].

Usually, KF is used to fuse accelerometer and gyroscope data to supply better prediction; for example, the use of KF in the detection of postural steadiness during quiet standing (e.g. standing in one spot without doing any other activity)[112]. KF has the potential for being used as a classification method on time sequence data by considering the errors from a family of KF models.

3.2.2 Markov chain

Markov chain is the simplest form of Markov model (Markov model is a random process model). It is a stochastic process defining a sequence of possible events according to Markov property, which implies that the probability of each event is determined only by the state attained in the previous event [113]. This means to find the best possible estimation for a process future state there is no need to know additional information about the process past state if its current state is known.

This characteristic results in reducing the number of parameters required for studying such a process [114]. When the state of a process is only partially observable the Markov chain will be called hidden Markov model. Markov chains are widely used to model many real-world processes. Ronao and Cho [115] proposed a two-stage hidden Markov model framework to recognise human activities using data collected from smartphone sensors. Their method achieved a classification accuracy of 93%. However, this method adds a computational complexity which results in consuming the mobile phone battery.

3.3 Chapter summary

This chapter has reviewed the literature related to the classification algorithms applied to the data that can be collected from accelerometer-based wearable sensors using healthcare monitoring systems in a residential environment. Machine learning algorithms were classified into two types: features based classification algorithms and sequence classification algorithms.

Most of these algorithms depend on extracting and use a number of features from the data. In addition, these algorithms use 50% or more of the data set for training which results in a more time-consuming process. Furthermore, the main issue with the previous classification work is dealing with the data without looking to the underlying cause of it.

This work extracts a small number of significant features from the data set to reduce the time required for the classification process. The research also explores a model-based approach for classification of human activities which may allow classification decisions to be understood and may enable more information to be derived from the classification process. In addition, the proposed method uses 15% of the data set for training which reduces the amount of the time required for the training process.

Chapter 4

Dynamic Systems

4.1 Introduction

Extracting useful information from a large amount of data, such as the data generated by wearable sensors, can be challenging. Machine learning algorithms offer significant tools for detecting and recognising activities and finding patterns in data [27, 110, 116, 117]. However, these algorithms do not consider the strong relationship between physical activity and the dynamic constraints on movement. There is a need for a fast, real-time and accurate approach to measuring human physical activities and performance when using wearable sensors data and using this data as part of a process of activity classification. To benefit from this approach, it is reasonable therefore to consider humans as a dynamic system.

A potential approach is by learning their dynamic features as a 'system identification task' and using the learned model both to predict future movements, and to classify activities. In the last two decades, there has been considerable work done on detecting, tracking, classification and recognition of human activities using camera data [118] and worn sensor data [27].

This chapter introduces the background theory on dynamic systems, with a focus on system identification that underpins the remainder of the work presented in this thesis.

4.2 Human movement representation

Human movement can be considered as a network of dynamic elements such as mass, muscle stiffness, and joint viscosity. There is much interest in dynamic human models as a method to understand human movement [119] but less work on model-based movement classification. Humans are nonlinear systems, but for simple movements the dynamics can be modelled in a linear form as for example:

$$m\ddot{y} \ + b\dot{y} \ + \ cy \ = \ f(t) \tag{4.1}$$

where m, b and c are constants loosely relating to mass, damping and stiffness, while y is the resulting position parameter, t is the time instance and f is the force. For this explanation $f(t)$ can be set to 0 in the absence of an external force effecting the movement, so

$$\ddot{y} \ = \ - \ \frac{b}{m}\dot{y} \ - \ \frac{c}{m}y \tag{4.2}$$

As the work performed in this thesis used an accelerometer sensor data, the acceleration ($\ddot{y}$) is 'predicted' by the velocity ($\dot{y}$) and position (y). This concept forms the basis for chapter 6. However, data is collected as a sequence of measurements and it is possible to show that a sampled version of this type of simple dynamic system is

$$y_n = -a_1 y_{n-1} - a_2 y_{n-2} \ \ldots \ - a_{n_a} y_{n-n_a}$$

where a_i are constants. This thesis must consider first that the system is not linear and second that acceleration measurements are in 3 axes, that is in the Cartesian x, y, z directions.

A simple extension is to consider simple polynomials, so models considered in this thesis will be of the following form:

$$x_n = -a_1 x_{n-1} - a_2 x_{n-2} \ ... \ - d_1 x_{n-1}^2 - d_2 x_{n-2}^2 \ ...$$

$$-b_1 y_{n-1} - b_2 y_{n-2} \ ... \ - e_1 y_{n-1}^2 - e_2 y_{n-2}^2 \ ...$$

$$-c_1 z_{n-1} - c_2 z_{n-2} \ ... \ - f_1 z_{n-1}^2 - f_2 z_{n-2}^2$$

4.3 A digital signal processing approach

4.3.1 Filter form

In signal processing, a filter is a process where data from the input (for example sensors) is computed; based on a limited set of past values, sometimes called the window length. The most common way of setting out the filter is the linear time invariant filter. Linear because scaling the input scales the output by the same amount. Time is invariant because results do not have an explicit absolute time, only times relative to the current output are considered.

Assume linear time invariant filter:

$$y_p = \frac{1}{a_0} \left(\sum_{k=0}^{N} b_k \ u_{p-k} \right) \ - \ \frac{1}{a_0} \left(\sum_{k=1}^{M} a_k \ y_{p-k} \right) \tag{4.3}$$

The operator q^{-1} can be used to simply delay the variable by one-time step, and likewise, the operator q will advance time by one-time step. Most work on filters treat the q operator in the same way as the z-transform. In practice, the q^{-1} operator simply represents storing the variable that is part of a `for` loop so it can be used on the next cycle of the loop. So, equation 4.3 can be written as:

$$a_0\ y_p\ =\ \sum_{k=0}^{N} b_k\ q^{-k}\ u_p\ -\ \sum_{k=1}^{M} a_k\ q^{-k}\ y_p \tag{4.4}$$

By expanding the summations, the filter form can be got.

$$\Big(a_0 + a_1 q^{-1} + a_2 q^{-2} + \cdots a_M q^{-M}\Big) y_p = \Big(b_0 + b_1 q^{-1} + b_2 q^{-2} + \cdots b_N q^{-N}\Big) u_p \tag{4.5}$$

$$a_0 y_p + a_1 y_{p-1} + a_2 y_{p-2} + \cdots a_M y_{p-M} = b_0 u_p + b_1 u_{p-1} + b_2 u_{p-2} + \cdots b_N u_{p-N} \tag{4.6}$$

Equations 4.3 and 4.4 could be equally well expressed as z-transforms. The choice of values for the parameters a and b are considered either as part of a filter design, or are estimated using system identification methods discussed in section 4.5.

Non-linear versions of these filters are commonly used to calculate features for machine learning methods. Calculations may have some relationship to the underlying system, for example calculating the standard deviation over the window period, but more often are simply chosen for their ability to discriminate data within a particular data set.

4.3.2 State space

In some circumstances, it is useful to consider a dynamic system in its state-space form. It is possible to show that the filter defined in equation 4.3 can also be expressed in a state-space form. The q operator, discussed in the previous subsection, can also be applied when considering a state space, but in this case, represents the value of a vector of states during the previous iteration of the `for` loop.

General definition of a dynamic system in state space is:

$$\dot{\underline{x}}\ =\ f(\underline{x})\ +\ v\ \ or\ \ \dot{\underline{x}}\ =\ f(\underline{x}, u)\ +\ v \tag{4.7}$$

Where v is a vector of noise.

Linear dynamic systems (filter form):

$$\dot{\underline{x}} \;=\; A\;\underline{x} \;+\; B\;u \;+\; v \tag{4.8}$$

Equations 4.7 and 4.8 represents a continuous time system, for example the position, velocity and accelerations of a person's centre of gravity. Once data has been measured by the accelerometer, gyroscope or other sensors, it is only available at discrete points in time.

4.3.2.1 Linear form of the (discrete) state space equations

The linear form of the sampled data state-space equations can be written as

$$\underline{\mathrm{x}}_{n+1} \;=\; A'\;\underline{\mathrm{x}}_n \;+\; B'\;\underline{\mathrm{u}}_n \tag{4.9}$$

where A' and B' are matrices. The state vector $\underline{x}_{n+1}$ either contains y_{n+1} or can be used to calculate y_{n+1}. Like the filter form in equation 4.3, the state space sampled equation can be expressed in discrete form as:

$$\underline{\mathrm{x}}_n \;=\; A'\;\underline{\mathrm{x}}_{n-1} \;+\; B'\;\underline{\mathrm{u}}_{n-1} \tag{4.10}$$

Using the q operator the equation 4.9 can be written as $qx = A'x + B'u$, and by multiplying by q^{-1} results $\underline{x} = A'q^{-1}\underline{x} + B'q^{-1}\underline{u}$, which on implementing the q operator becomes equation 4.10

4.4 Dynamic models of type $y = \varphi^T\theta$

This formulates the data prediction of y_n based on data up to and including y_{n-1}. The concise form of the filter equation 4.3 is thus

$$y_n = \varphi_n^T\theta \tag{4.11}$$

Where $\varphi_n^T = [y_{n-1}\ y_{n-2}\ ...\ y_{n-m}]$ and $\theta = [a_1\ a_2\ ...\ a_m]$.
θ thus is a model of the dynamic system.
This form of the equation is common in a systems identification approach to system modelling.

4.5 System identification

Systems are objects that can be studied, controlled and affected their behaviour by the human [120, 121]. To achieve these tasks, it is necessary to have a model of the system. The model is the knowledge of the system's characteristics. A model could be given in different forms, e.g verbal, graphical or mathematical form. The mathematical model can be constructed in a way called system identification, which is the field that uses experimental data for modelling dynamic systems. Figure 4.1 depicts a simple structure of a dynamical system. Where $u(t)$ is a control input to the system, $v(t)$ is uncontrolled input and $y(t)$ is the system output that can be measured and provides information about the system. In a dynamical system, the input at time t will affect the output at time instants $s > t$. Note previous values of y and u are available within the system as indicated by equation 4.3
The following section will present one of system identification algorithms which will be considered in chapter 5 for human activity classification purpose.

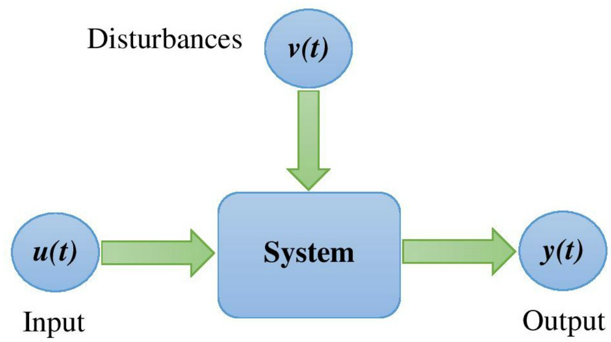


Figure 4.1: A dynamical system with input u(t), output y(t) and disturbance v(t), where t denotes time.

4.6 Recursive least square algorithm with a forgetting factor (RLSF)

RLS is the recursive form of the least-squares regression algorithm. To model the observed system, RLS algorithm takes each new data point in account to correct the previous estimation of parameters from some linearized correlation thought [122]. This approach allows for the dynamical application of least squares to time series collected in real-time [122]. The classic RLSF algorithm is expressed in the following equations [123][124]:

$$\hat{\theta}(n) = \hat{\theta}(n-1) + K(n)\,\varepsilon(n) \tag{4.12}$$

$$\epsilon(n) = y(n) - \varphi^T(n)\,\hat{\theta}(n-1) \tag{4.13}$$

$$K(n) = P(n)\,\varphi(n) = \frac{P(n-1)\,\varphi(n)}{\lambda + \varphi^T(n)\,P(n-1)\,\varphi(n)} \tag{4.14}$$

$$P(n) = \frac{1}{\lambda}\Big(P(n-1) - \frac{P(n-1)\,\varphi(n)\,\varphi^T(n)\,P(n-1)}{\lambda + \varphi^T(n)\,P(n-1)\,\varphi(n)} \tag{4.15}$$

Where $\hat{\theta}(n)$ is the model parameter vector at time instance n. $\hat{\theta}(n-1)$ is the model based on past information. $\varphi(n)$ is a vector of input values. $\varepsilon(n)$ is a prediction error, which is the difference between the measured output $y(n)$ and the one step ahead prediction $\hat{y}(n)$ made at time $(n-1)$.

$$\hat{y}(n|n-1, \hat{\theta}(n-1)) = \varphi^T \hat{\theta}(n-1)$$

$K(n)$ is a weighting factor that shows how much the different elements of the parameter vector will be modified by the $\varepsilon(n)$ value. λ is the forgetting factor which is added to the RLS to reduce the effect of the previous inputs and give more priority to the new input. The algorithm needs to initialise values for $\hat{\theta}(0)$ and $P(0)$. It is preferable to initial $\hat{\theta}(0) = 0$ and $P(0) = LN \times I$, where LN is a large number and I is the identity matrix.

Figure 4.2 depicts a visualisation of the estimation process. In this figure, an estima-

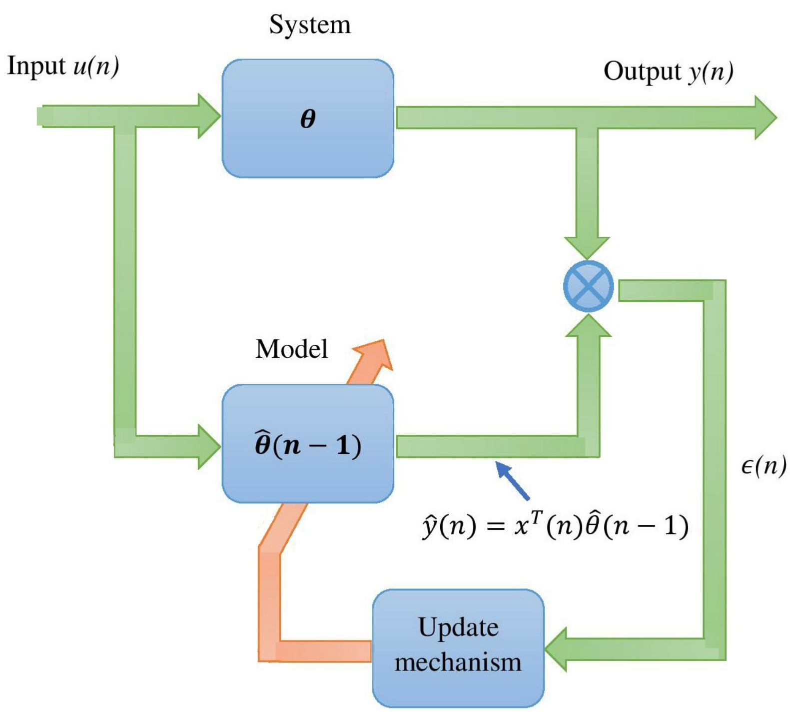


Figure 4.2: A visualisation of an iterative process of recursive estimation in which an update mechanism is used to adjust model parameters. This mechanism computed from a measure of the quality of the model which is, in this model, is indicated by the error $\varepsilon(n)$, redrawn from [3].

tion $\hat{y}(n)$ of the current output could be obtained using the model based on previous information $\hat{\theta}(n-1)$. By comparing this estimation with the observed output $y(n)$ an error $\varepsilon(n)$ will be generated. This, in turn, gives an update to the model by correcting $\hat{\theta}(n-1)$ to the new value $\hat{\theta}(n)$. The recursive 'predictor-corrector' structure permits considerable saving in computation.

Instead of recalculating the least-squares estimation in its entirety, which needs storing of all previous data, it is both efficient and suitable to solely store the 'previous' estimate calculated at time n, that is $\hat{\theta}(n)$, and by involve the new observation only in the updating step the 'new' estimates $\hat{\theta}(n+1)$ will be acquired. This approach allows us to build the best representation of the data models for use in the proposed model-based methods illustrated in chapter 6.

Chapter 5

Mapping acceleration data to a sphere to extract relevant features for human activity classification

5.1 Introduction

A considerable number of methods have been investigated in the literature for ADL classification using different types of algorithms, as was described in section 2.2.

Many data sets relating to human activities were collected globally [1, 24, 125, 126, 127, 128].

However, the availability, nature and quality of these data sets highly varied. There is a substantial need for a real data set to be publicly available. However, this is not always possible because there may be many restrictions. To collect such a data set, it could be expensive and difficult. In addition to this, there can be ethical constraints to make the data publicly available. The availability of such a data set would provide a chance for researchers to validate other's work, expand it, and perform direct comparisons between the performances of various methods [1, 129].

The most important part that the method efficiency depends on is the features extracted from the data set. Extracting useful features that increase the efficiency of classifications algorithms is one of the objectives of this chapter. It describes the extraction and implementation of new features and comparing the result with the work of state-of-art methods.

This chapter is an expanded version of the work published in [21]. All the experiments achieved in this chapter and chapter 6 were coded in MATLAB R2018 and run on a PC machine with an Intel core i5 6200U, CPU 2.4 GHz and 8 GB RAM.

5.2 Data source

Two data sets were used for this work. The first data set is from the EPSRC funded SPHERE project lead by the University of Bristol, which will be discussed in section 5.2.1. The second data set is a public data set from Fredrick-Alexander University, which used to compare method of this work with other methods in the literature. Both data sets will be described in the following subsections.

5.2.1 SPHERE research project data set

The SPHERE research project (http://irc-sphere.ac.uk) aimed to deploy, collect and analyse data from a range of sensors (including cameras to identify only a person's profile, environmental sensors measuring room occupancy, energy and water usage, and room temperature and wearable inertial sensors) in 100 residential homes in the Bristol area.

Funded by the EPSRC, SPHERE was a 5 year project to investigate the acquisition and analysis of information that may be relevant in healthcare management. The research focused on individuals in residential environments. The main project was completed in April 2019 with a follow on project starting shortly afterwards. One key aspect of this research was to consider the data analysis and data mining techniques that will enable this data to be used by the individuals, their carers, and researchers to monitor healthcare related problems [11, 130, 131].

The project was not limited to specific healthcare needs but could include COPD (chronic obstructive pulmonary disease), Parkinson's disease, stroke, frailty, depression, sleep disorders, and obesity [11]. For data collection, the SPHERE research included body-worn sensors that could operate for up to six months without re-charging while transmitting key information to the house infrastructure for data storage and analysis [130, 131].

In preparation for deployment to residential houses in the Bristol area, the University of Southampton collected data for SPHERE project from a small cohort of individuals with Parkinson's disease in Southampton using bespoke wearable sensors [132]. Several data sets were collected and archived. This work uses the data set known as *"Bridge"*, which was collected from 5 individuals in a residential environment over three sessions for a period of approximately 1-2 hours on different days, and under an ethics protocol approved by the University of Southampton.

Inertial sensors were placed on the person's wrists, ankles and waist at the lower back. Each sensor consist of a triaxial accelerometer with sampling rate set to 50 Hz and triaxial gyroscope. The individuals were asked to perform various activities such as sitting in a chair, standing, sit to stand, stand to sit, walking, stairs up, stairs down and turning.

The data was processed with the Elan software package to associate the data streams with specific activities. For the work presented in this report, only a data of one participant of this data-set was used, which was coded as *Mr T* data. The reason for selecting this participant's data rather the others was because it's contain an uninterrupted sequence of data that covered all of the activities listed above in best sequence and iterations. Although participants wore sensors on wrists, ankles and waist, just the waist worn sensor data was used in this work.

5.2.2 Public data set of Fredrick-Alexander University

A second data set called *"Bench Mark"* data set was used in this work. *"Bench Mark"* data set is available from (http://www.activitynet.org). This data set was collected by Leutheuser et la. [1] as a public data set for a research. Leutheuser et al. use their data set to compare their proposed activity classification method with a number of other classification methods for classifying of Activities of Daily Living (ADL).

This data set was collected from 19 young healthy individuals (age 20 to 34 years, 8 female and 11 male) in controlled conditions in the laboratory. The participants were asked by the researchers to perform 13 activities, which were sitting, lying, standing, washing dishes, vacuuming, sweeping, walking outside, ascending stairs, descending stairs, treadmill running (with speed set to 8.3 km/h) bicycling on an ergometer (with two different resistance levels 50 W and 100 W), and rope jumping. The collection period was approximately 1-2 minute(s) for each activity.

Four inertial sensors with triaxial accelerometers with sampling rate set to 204.8 Hz and triaxial gyroscope were used. These sensors were placed on right wrist, right hip, left ankle and chest. The data of all participants and all sensors were used in this work.

5.3 Methods used

The methods presented in this research were for extracting useful features from the data of accelerometer sensor; and apply them on the *Bridge* and the *Bench Mark* data sets, that illustrated in section 5.2.1 and section 5.2.2 respectively.

5.3.1 Computation of meaningful features

The data analysis recognises that the principal measured component from accelerometer data is the omnipresent $1g$ field. Thus, features relating to angle and magnitude with respect to this field dominate, and movement activities are effectively imposed on this data. Data from the waist sensor of a single individual from *Bridge* data set (i.e. *Mr T*) was used for preliminary analysis. The data was initially processed by considering the principal movements of the individual to be in the 'sagittal plane' (i.e. forwards and backwards). For that a measure of jerk (the derivative of acceleration) was estimated. If ($\underline{\mathrm{a}}_n$) is acceleration at sample (n), then jerk (J) can be considered as the following:

$$\underline{\mathrm{J}}_n \approx \frac{1}{T}(\underline{\mathrm{a}}_n - \underline{\mathrm{a}}_{n-1}) \tag{5.1}$$

Where (T) is the time between the samples (a_n and a_{n-1}).

The acceleration consists of that due to the individual's movements and gravity i.e.

$$\underline{\mathrm{a}}_n = \underline{\mathrm{b}}_n + \underline{\mathrm{g}}_n \tag{5.2}$$

Where (b_n) is the acceleration due to the person's movement and (g_n) is gravity.

So that jerk of the person's movements is:

$$\underline{\mathrm{J}}_n = \frac{1}{T}(\underline{\mathrm{b}}_n - \underline{\mathrm{b}}_{n-1}) = \frac{1}{T}(\underline{\mathrm{a}}_n - \underline{\mathrm{g}}_n - \underline{\mathrm{a}}_{n-1} + \underline{\mathrm{g}}_{n-1}) \approx \frac{1}{T}(\underline{\mathrm{a}}_n - \underline{\mathrm{a}}_{n-1}) \tag{5.3}$$

since gravity is constant. A scalar estimate of movement was also considered that loosely relates to jerk is possible by calculating the dot product of the unit vector.

So $\left(F_n = \frac{\underline{\mathrm{a}}_n}{|\underline{\mathrm{a}}_n|} \cdot \frac{\underline{\mathrm{a}}_{n-1}}{|\underline{\mathrm{a}}_{n-1}|}\right)$ gives a scalar feature for each (n) such that if ($\underline{\mathrm{a}}_n = \underline{\mathrm{a}}_{n-1}$) then ($F_n = 1$), but for any movement it will be $\left(\frac{\underline{\mathrm{a}}_n}{|\underline{\mathrm{a}}_n|} \cdot \frac{\underline{\mathrm{a}}_{n-1}}{|\underline{\mathrm{a}}_{n-1}|}\right)$ i.e. reduced by an amount relating to the angle between these two unit vectors. During periods of low movement such as sitting, standing or sleeping, the person's acceleration ($\underline{b}_n$) will be small when compared to ($\underline{g}$), so we can use the component of ($\underline{g}$) to estimate accelerometer orientation, resting periods will relate to magnitude of acceleration to the magnitude of ($\underline{g}_n$):

$$|\underline{g}_n| = |\underline{a}_n - \underline{b}_n| \approx |\underline{a}_n| \tag{5.4}$$

If the accelerometer is approximately aligned in the sagittal plan (a two dimensional) assumption of orientation can be made, i.e. movement is primarily in the $(X \cdot Y)$ plane. So orientation with respect to the ($\underline{x}$) axis of the accelerometer is given by:

$$X_{acc} = \underline{g}_n \cdot \hat{\underline{x}}_n = |\underline{g}_n| \cdot \cos\ \theta \tag{5.5}$$

$$Y_{acc} = \underline{g}_n \cdot \hat{\underline{y}}_n = |\underline{g}_n| \cdot \sin\ \theta \tag{5.6}$$

Where (θ) is the angle between ($\underline{g}_n$) and the X axis of the accelerometer and (X_{acc}) is the acceleration component along the X axis.

So using equations 5.5 and 5.6 (θ), it can be estimated as $\left(\tan\theta = \frac{|g|\sin\theta}{|g|\cos\theta} = \frac{Y_{acc}}{X_{acc}}\right)$.

So (θ) can also be estimated as ($\theta = atan2(Y_{acc}, X_{acc})$).

This represents an acceleration with respect to a unit gravity sphere, a concept that is explored in section 5.4.1 of this chapter. Figure 5.1 shows the accelerometer's axes and the gravity vector as a two dimensional, i.e. sagittal plan pose.

According to equation 5.6 the angle between the gravity vector and the pose of the individual's trunk (θ) was computed using the arctangent ('**atan2**' function). The accelerometer axes that used as arguments for '$atan2$' function are the vertical axis and the axis that points either forwards or backwards. To extract the features and to determine the best window size and window type, a non-sliding and sliding windows

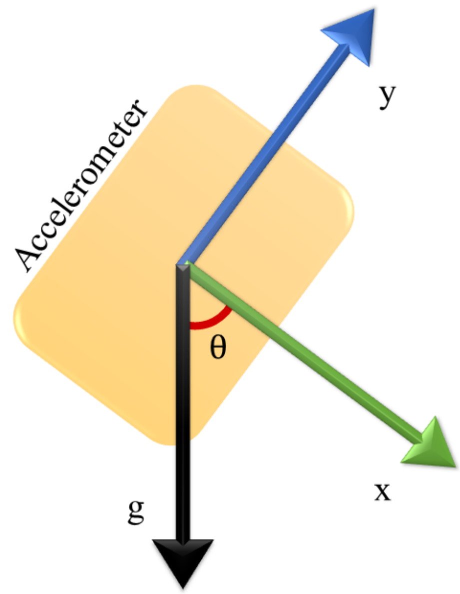


Figure 5.1: A diagram of accelerometer's axes (x & y) and the gravity considered in two dimension (i.e. sagittal plane movement).

of sizes 24, 48, 72, 96, 144, 192 and 240 n data samples with 50% overlap were used. These window sizes represented approximately 0.5, 1, 1.5, 2, 3, 4 and 5 seconds of data. For classification of activities, three features were extracted for each widow which are mean, standard deviation and energy. The energy $\mathscr{E}$ is computed by adding together the sum of the squared values for each axis, divided the addition result by three then divided by the number of samples, as in the following equation:

$$\mathscr{E} = \Big(\sum_{i=1}^{n} (x_i^2 + y_i^2 + z_i^2) \Big) \frac{1}{3n} \tag{5.7}$$

Where n is the sample window size; and x, y & z is the axes of the accelerometer. Classification was performed using Decision trees (DTs) and Naïve Bayes (NB) classification methods separately, and validated using 10 fold Cross Validation method. Classification results are shown in section 5.4 of this chapter.

5.4 Results already obtained

5.4.1 Evaluation of activity using DTs, NB and kNN classifiers

The obtained results from both of the classification methods show that the 48 sample sliding window has better classification accuracy than the other windows, with 79% accuracy for DTs and 85% for NB. Table 5.1 shows that NB outperform DTs in recognition of five activities which are the ambulation acts. While the best results for stationary acts gained by TDs.

Table 5.1: Classification accuracy (in per cent) for DTs and NB (Parkinson's disease) using Bridge's data set. The results marked by bold indicate the higher classification accuracy.

Activities	**DTs**	**NB**
Sitting	**99.63**	96.08
Standing	**98.35**	97.69
Sit to Stand	68.75	**75.00**
Stand to Sit	66.67	66.67
Walking	90.91	**95.04**
Stairs-up	87.50	**100.00**
Stairs-down	66.67	**77.78**
Turning	50.00	**75.00**
Overall Accuracy	78.56	**85.41**

As a result of the success of the '$atan2$' function, additional analysis was considered to allow increase the veracity of the classification of activities. This was done by using a new method for the visualisation of the accelerometer data. Instead of plotting the data point in two or three dimensions, the new method considered the plotting of the gravity vector with respect to a sphere of radius $1g$ in three dimensions.

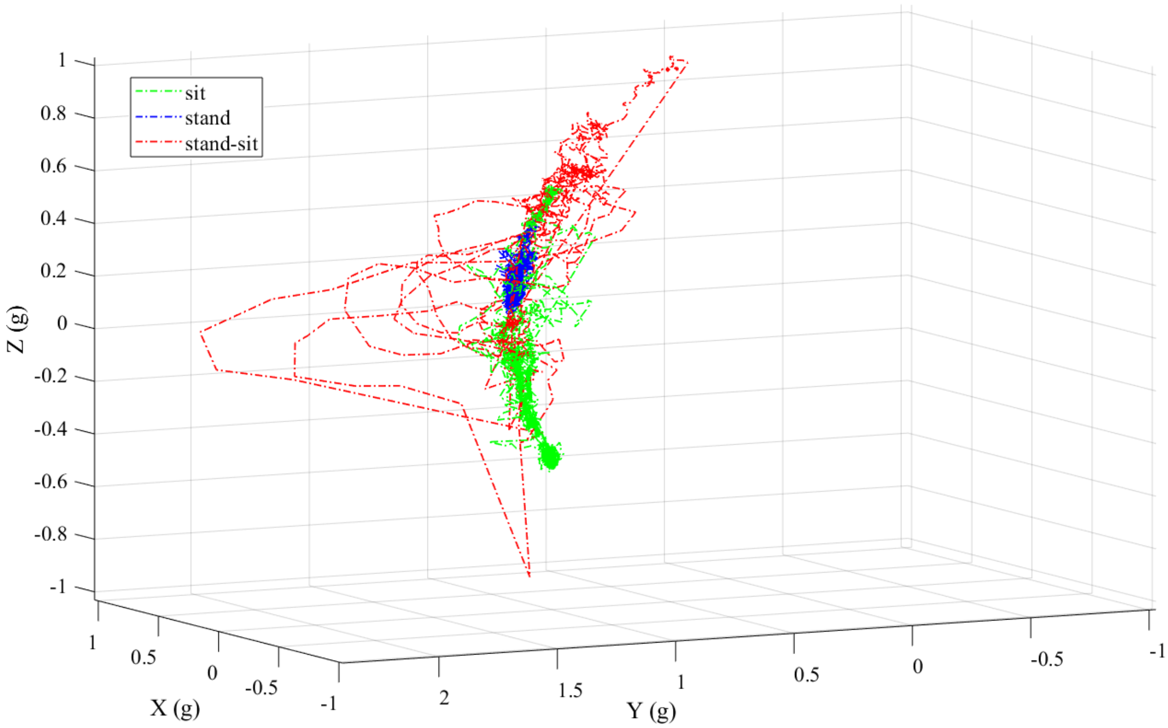
Figures 5.2a and 5.2b show the plotting of accelerometer data of three of the *Bridge (Mr T)* data set labelled activities (sitting, standing, and stand-to-sit) without the sphere and onto the sphere respectively. As shown in Figure 5.2b, it is noticeable that static and slow movements are characterised by points on or near the surface of this sphere, and more dynamic movements are characterised by signature trajectories above or below the surface of the sphere. Such characteristics can't be observed in Figure 5.2a. Observation of these activities indicates that the use of the dot product of successive acceleration vectors should be significantly useful in increasing the accuracy of the classification algorithm.

The *Bench Mark* data set of Leutheuser et al [1] was also used to examine the features gained using both 'atan2' function and dot product operation; and for comparison with Leutheuser's hierarchical classification approach.

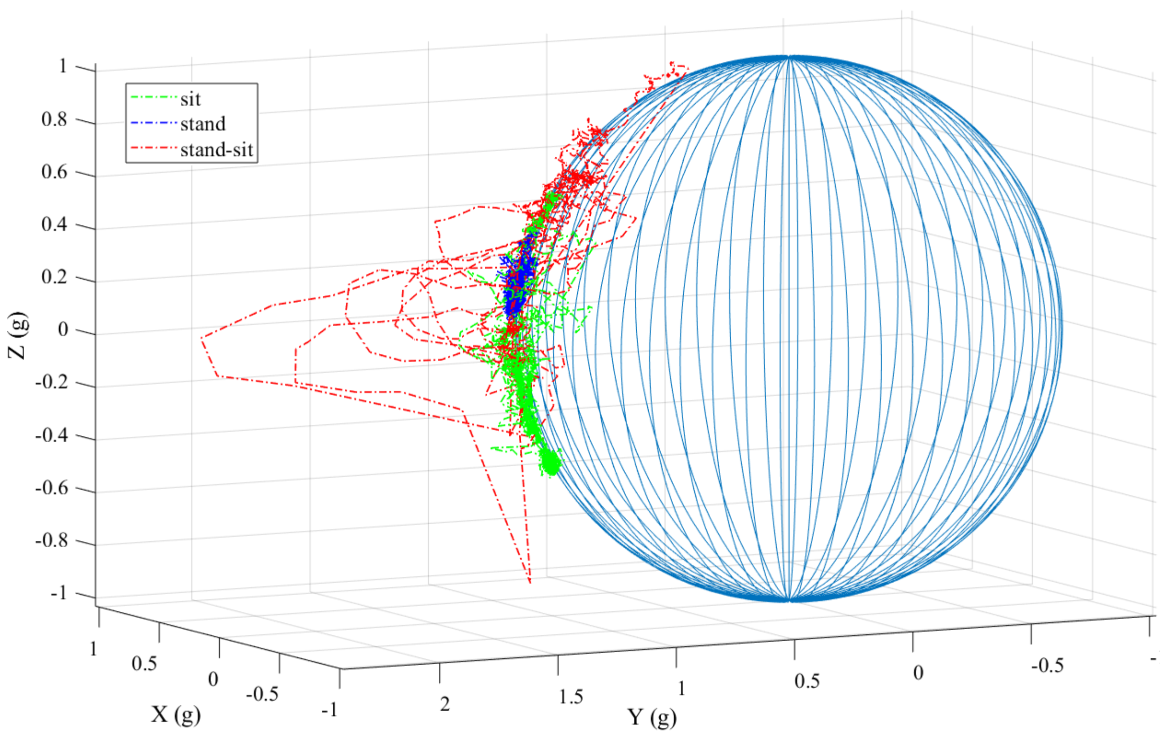
As mentioned in section 5.2.2, the *Bench Mark* data set was collected using four sensors with a 204.8 Hz accelerometer and gyroscope from 19 subjects achieved 13 activities. Leutheuser et al. [1] used a hierarchical classification method which included AdaBoost (ADA), classification and regression tree (CART), kNN and SVM. They used a sliding window of 5 second size with a 50% overlap for analysis of the *Bench Mark* data set. For each window, the total number of features extracted and used by the researchers was 152 features for dynamic activities and 12 features for static activities.

All of the four sensors from the *Bench Mark* data set were used in our analysis. Both of 'atan2' function and dot product operation were used to compute features from these four accelerometer sensors. Because the sensors placed on limbs tend to have a greater range of movement, the atan2 function was computed for each pair of axes on each of the 4 sensors. This results in three values for every accelerometer.

For feature extraction and to determine the best window size, a sliding window of size 204, 408, 612, 816, 1020 and 1224 samples was used. This nearly corresponds to 1, 2, 3, 4, 5 & 6 seconds respectively, with a 50% overlap. For classification, three features were



(a) Plotting the data without the sphere.



(b) Plotting the data onto the sphere. Data points away from the sphere represent the accelerations needed during movement.

Figure 5.2: Visualisation of the waist accelerometer sensor data for sitting, stand to sit and standing activities.

extracted for each accelerometer which are mean, standard deviation and energy; and mean for every gyroscope axis and energy for each gyroscope (the energy was computed as illustrated in section 5.3.1, equation 5.7).

The total number of features used in this work for all the four sensors is 52 features. The classification was performed using DTs, NB and kNN classification methods separately, and validated using 10 fold Cross Validation method.

The results obtained from DTs, NB and kNN classification methods with the results of Leutheuser et al approach [1] are shown in Table 5.2. The results show that for DTs the 408 samples (nearly 2s), NB the 1020 samples (nearly 5s) and kNN the 1020 samples (nearly 5s) sliding windows have better classification accuracy than the other windows, with overall accuracy 91.38% for DTs, 79.22% for NB and 78.36% for kNN. The results shown in this table and in Table 5.1 will be discussed in section 5.4.2.

Table 5.2: Classification accuracy for 13 activities and overall accuracy for DTs, NB, kNN and [1], using the *Bench Mark* dataset. The results in bold have highest classification accuracy.

Activities	**Proposed DTs**	**Proposed NB**	**Proposed kNN**	**Results from [1]**
Sitting	**97.1**	13.19	70.77	88.9
Lying	98.87	95.22	83.7	**100.0**
Standing	**96.92**	89.23	79.78	89.8
Washing Dishes	95.75	96.91	92.02	**98.1**
Vacuuming	78.08	**90.61**	57.64	85.4
Sweeping	82.74	69.62	72.18	**89.9**
Walking	97.04	94.38	94.29	**99.0**
Ascending Stairs	86.03	93.75	54.69	**95.5**
Descending Stairs	83.38	88.09	58.84	**95.2**
Treadmill Running	99.13	98.03	97.27	**100.0**
Bicycling on Ergometer (50 W)	**86.85**	7.24	80.65	69.1
Bicycling on Ergometer (100 W)	87.83	**95.91**	81.05	53.5
Rope Jumping	98.18	97.71	95.8	**100.0**
Overall Accuracy	**91.38**	79.22	78.36	89.6

5.4.2 Analysis of results and discussion

In this work, three classification algorithms (Decision Trees (DTs), Naïve Bayes (NB) and k Nearest Neighbour (kNN)) were applied separately to examine the usefulness of this proposed method to extract meaningful features of movement (dot product of acceleration and atan2). These features were used to classify activities for an individual with Parkinson's disease; and also as a direct comparison to published *Bench Mark* data from [1].

The application of DTs and NB on the waist sensor data of a single individual with Parkinson's disease has shown the advantage of the NB algorithm over the DTs algorithm for these features, with 85.41% and 78.56% overall accuracy respectively.

As outlined in Table 5.1, from the eight activities in the data set, DTs had the best classification accuracy when compared to NB for sitting and standing activities whereas NB outperformed DTs in recognition of success for the five dynamic activities. However, performing the three classification algorithms DTs, NB and kNN on a *Bench Mark* dataset using four sensors (placed on the right wrist, right hip, left ankle and chest) for 19 individuals, results in outperforming of DTs algorithm over NB and kNN algorithms. As shown in Table 5.2, the failure of the NB algorithm was in recognition of sitting, sweeping and bicycling ergo-meter (50) activities, with classification accuracy 13.19%, 69.62% and 7.24% for each of them respectively. The reason for these poor results is that the misclassification particularly of SI (sitting), SW (sweeping), and BC50 (bicycle ergo-meter at 50 W resistance level) by the NB algorithm as shown in Table 5.3.

The uncertainty of NB appears to be between two stationary acts, [sitting and standing] and between the matched repetitive higher-speed acts, [vacuuming and sweeping, bicycling ergo-meter (50 W) and bicycling ergo-meter (100 W)]. This could be because it needs more data for training.

For the same reason, the kNN classification method had lower classification accuracy comparing to DTs. As shown in Table 5.4, the misclassification is obvious between the dynamic repetitive acts. That is between [vacuuming and sweeping], [walking, ascending stairs and descending stairs] and [bicycling ergo-meter (50 W) and bicycling ergo-meter (100 W)].

There was a high classification accuracy of DTs, so the confusion matrix has not been shown. It is possible that this classification accuracy may be due to the correlations in features values that are picked up by the rule-based activity recognition of DTs.

For instance, the DTs classified sitting and standing as activities having different angles between the individual's trunk and gravity vector at the hip and low velocity at the hip, wrist and ankle sensors. It distinguishes bicycling (50 W) activity from bicycling (100 W) activity because each one of them involves different levels of velocity (moderate and high) at the ankle sensor.

Also, it differentiates between sweeping and vacuuming, even though both activities show high energy in wrist acceleration because the two activities are characterised by different gravitational angles in the wrist sensor. The weaker performance of NB and kNN approaches may be due to their inability to adequately model such rules.

Comparing these results with the approach of Leutheuser et al [1], it can be noted that although the DTs method had an overall classification accuracy that is higher than the results shown in [1], the latter outperforms the DTs method in specific recognition of eight of the thirteen activities. The better individual recognition results of [1] are probably due to the hierarchical approach used.

This approach divided the thirteen activities into groups and use an SVM for the initial group classification and different algorithms to do the sub-group classification. However, for this data set, this approach had a low classification accuracy for sitting, standing, bicycling (50 W) and bicycling (100 W).

In addition, this approach used 152 features for each sliding window of dynamic activities. While our proposed method uses just 52 features for each sliding window. The high number of features could result in more computational complexity in real-time systems.

Table 5.3: Confusion matrix for the NB algorithm of the proposed method. Coloured numbers highlight the misclassification of key activities. Columns are the actual classes and rows are the predicted classes.

	SI	**LY**	**ST**	**WD**	**VC**	**SW**	**WK**	**AS**	**DS**	**RU**	**BC 50**	**BC 100**	**RJ**
Sitting (SI)	**60**	7	6	0	1	2	0	0	0	0	2	0	2
Lying (LY)	45	**439**	2	0	0	0	0	0	0	0	0	0	0
Standing (ST)	316	14	**410**	7	6	0	0	0	0	0	0	0	0
Washing-Dishes (WD)	7	0	27	**912**	5	3	0	0	0	0	0	0	0
Vacuuming (VC)	2	0	7	10	**415**	196	6	0	0	0	2	0	0
Sweeping(SW)	3	0	3	11	28	**516**	18	0	0	1	5	8	0
Walking (WK)	0	0	0	0	0	1	**1933**	16	3	2	3	1	0
Ascending Stairs (AS)	0	0	0	0	1	10	32	**300**	26	0	4	1	0
Descending Stairs (DS)	0	0	0	0	2	15	57	4	**244**	9	1	0	0
Treadmill Running (RU)	0	0	0	0	0	0	2	0	1	**897**	25	0	0
Bicycling 50 (BC 50)	0	0	0	0	0	0	0	0	0	0	**68**	33	3
Bicycling 100 (BC 100)	0	0	0	0	0	1	0	0	0	0	814	**886**	1
Rope Jumping (RJ)	22	0	0	0	0	0	0	0	3	6	1	0	**256**

Table 5.4: Confusion matrix for the kNN algorithm of the proposed method. Coloured numbers highlight the misclassification of key activities. Columns are the actual classes and rows are the predicted classes.

	SI	**LY**	**ST**	**WD**	**VC**	**SW**	**WK**	**AS**	**DS**	**RU**	**BC 50**	**BC 100**	**RJ**
Sitting (SI)	**322**	35	20	17	4	5	2	0	0	0	0	0	6
Lying (LY)	43	**385**	24	4	1	1	1	0	0	0	0	0	0
Standing (ST)	25	27	**363**	42	2	4	0	0	0	0	0	0	0
Washing-Dishes (WD)	28	8	39	**865**	9	10	0	0	0	0	0	1	0
Vacuuming (VC)	6	4	4	4	**264**	**135**	5	4	1	0	7	2	1
Sweeping(SW)	9	0	4	8	**149**	**537**	7	23	3	0	14	15	2
Walking (WK)	1	0	0	0	8	8	**1931**	**56**	**62**	11	3	2	0
Ascending Stairs (AS)	0	0	0	0	6	18	42	**175**	**46**	1	6	5	0
Descending Stairs (DS)	0	0	0	0	1	3	**48**	46	**163**	3	6	0	0
Treadmill Running (RU)	0	0	0	0	0	1	6	1	2	**890**	14	0	0
Bicycling 50 (BC 50)	0	1	1	0	9	12	2	7	0	9	**746**	**151**	1
Bicycling 100 (BC 100)	0	0	0	0	5	10	4	8	0	0	**127**	**753**	1
Rope Jumping (RJ)	21	0	0	0	0	0	0	0	0	1	2	0	**251**

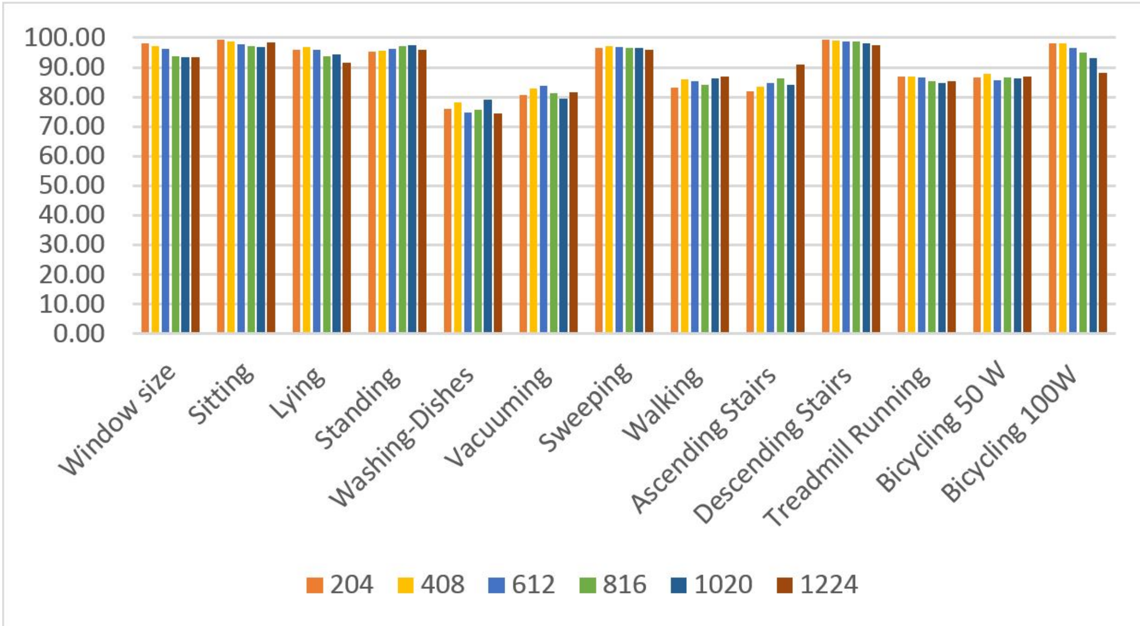


Figure 5.3: Using *Bench Mark* dataset, DTs accuracy of all sensors for all the 13 activities with different sampling window size.

Nevertheless, this method has been applied to two different data sets, one acquired from an individual with Parkinson's disease and the other from 19 young healthy individuals. The results show that the use of a number of sensors with both accelerometer and gyroscope has a substantial impact on the classification accuracy for all activities rather than the use of a single accelerometer sensor. An improvement in the proposed method might be achieved by exploiting a number of classification algorithms.

Figure 5.3 shows the classification accuracies for DTs for the 13 activities using a number of sampling window sizes. It is clear that for some activities the use of small window size results in best classification accuracy, such as sitting and lying. For other activities, the larger size the better result, such as walking and ascending stairs; while this does not make a difference for some other activities, such as sweeping.

For that, the use of a combination of different classification algorithms applied to the proposed features with different window sizes may result in higher classification accuracy as well as real-time recognition system for activities of daily living (ADL). There is a difference between window sizes of the DTs and NB to achieve the best results from both the Bridge and the *Bench Mark* data sets. There are many possible causes but it should be noted that the Parkinson's data set was collected in a home environment while the *Bench Mark* data collected in a purpose built laboratory.

Furthermore, for more analysis, the data of three static activities (sitting, standing and lying) of the hip accelerometer sensor of *Bench Mark* dataset for 14 participants was visualised by plotting onto a sphere of radius 1g.

This results in, for each activity, the data points of all participants located in a specific region onto the sphere, as shown in Figure 5.4. In the same way, Figures 5.5 and 5.6 show the projection of the 14 participants and two other participants' data onto the sphere for sitting and lying activities respectively. As appears in Figures 5.5 and 5.6, the data points of the new participants are located in different regions far from the region of the other 14 participants.

This might be due to a misalignment of the hip sensor of those two participants, which raises the issues to detect and correct the data of misalignment sensors in order to avoid the misclassification of activities. This could be achieved by considering the region of the other data of correct alignment sensors.

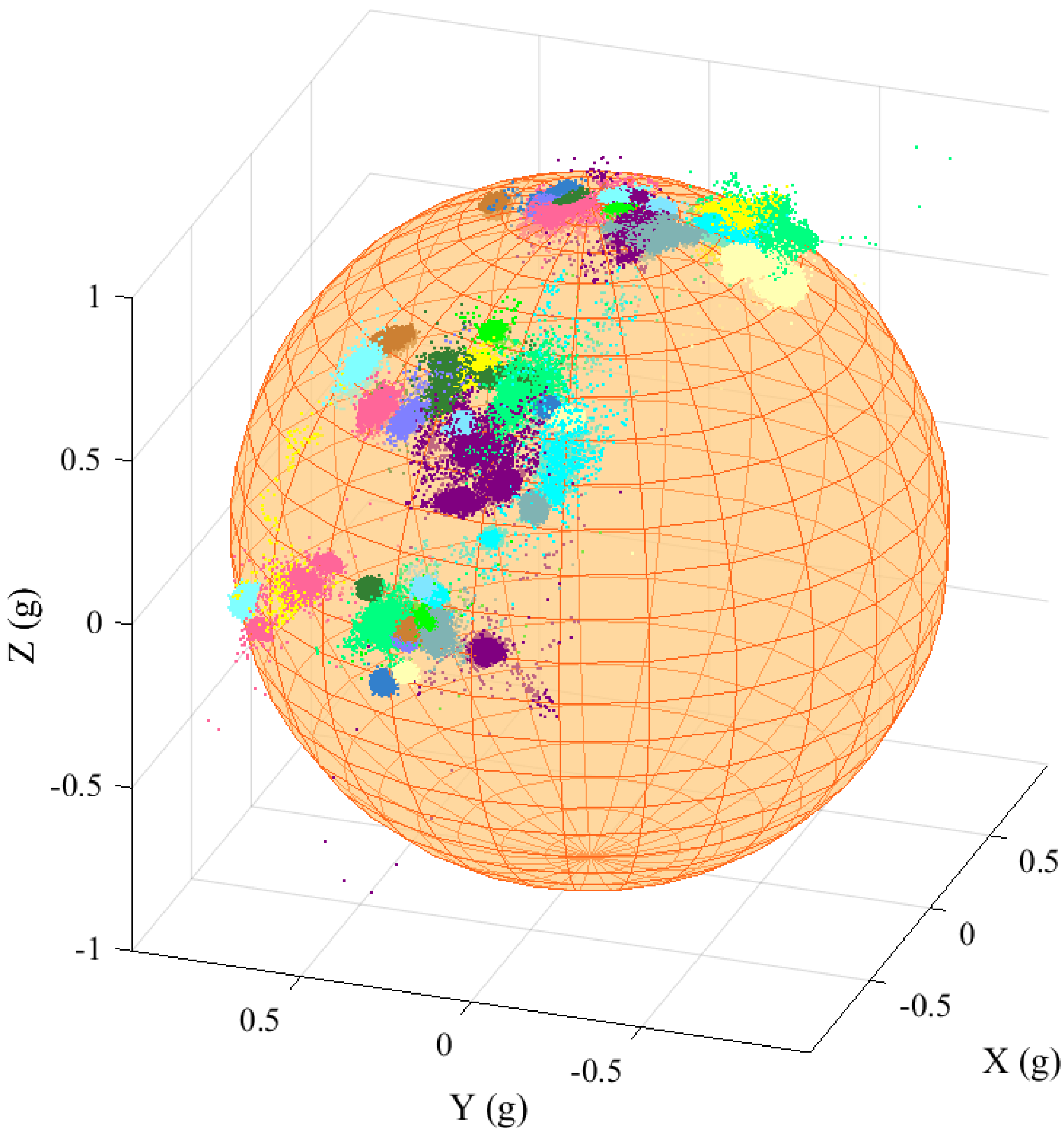


Figure 5.4: Plotting of the *Bench Mark* dataset hip accelerometer sensor data of 14 participants for sitting, lying and standing activities onto the sphere. The colours represent different participants.

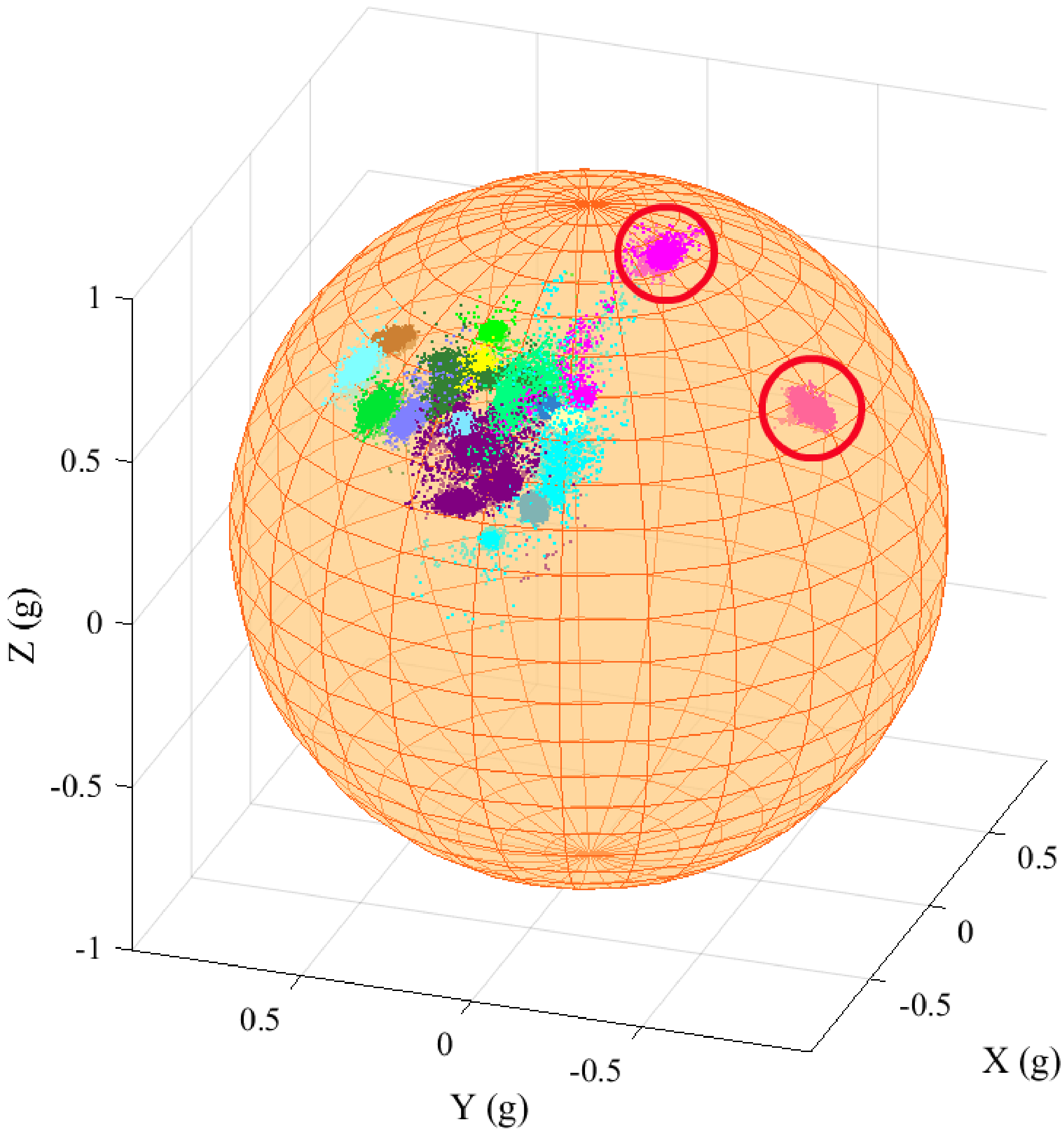


Figure 5.5: Plotting of the *Bench Mark* data set hip accelerometer sensor data of 16 participants for sitting activity onto the sphere. Each colour represents a different participant. The highlighted data points belong to the data of misalignment sensors.

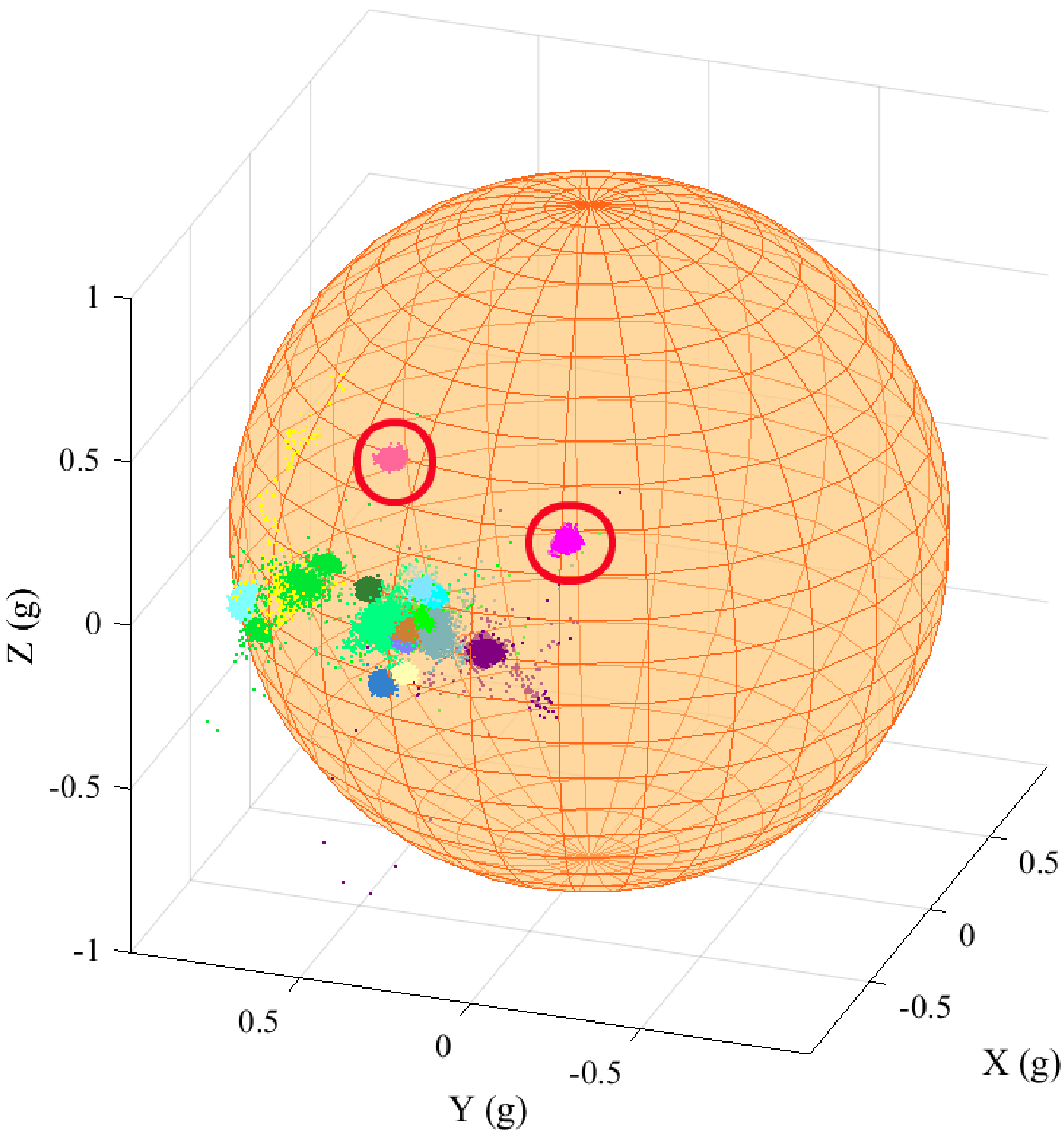


Figure 5.6: Plotting of the *Bench Mark* dataset hip accelerometer sensor data of 16 participants for lying activity onto the sphere. Each colour represents a different participant. The highlighted data points belong to the data of misalignment sensors.

Table 5.5: Classification accuracy for 13 activities for each sensor and all sensors using DTs, NB and kNN, on the *Bench Mark* dataset. The bolded results indicate the higher classification accuracy (in per cent) for each sensor, and the underlined results indicate the higher classification accuracy for each classification method. The sliding window is the sampling rate in (Hz).

Sensor	**Classification Algorithms**					
	DTs		**NB**		**kNN**	
	Window Size	**Accuracy**	**Window Size**	**Accuracy**	**Window Size**	**Accuracy**
Right Hip	816	<u>**83.3**</u>	1224	60.43	612	61.34
Right Wrist	612	**76.36**	1224	56.32	204	49.33
Left Ankle	1020	**82.62**	1224	<u>68.32</u>	204	<u>65.28</u>
Chest	1224	**80.38**	1224	63.79	1020	52.13
All Sensors	408	**91.38**	1020	79.22	1020	78.36

In addition, to determine the best location for the sensor on the individual body, a comparison experiment was carried out using the *Bench Mark* data set with the same previous specifications (i.e. sliding window sizes, extracted features, classification algorithms and validation method).

The results are shown in Table 5.5, which presents the higher overall accuracy sliding window sizes for each classification method and each sensor. It is obvious that DTs has the best classification accuracy for every single sensor, where both NB and kNN have poor accuracy. Although using the data of the right hip sensor results in higher classification accuracy (i.e. exceed 83%) than the other sensors, it is clear that the accuracy of using all sensors is highest.

Figure 5.7 shows the accuracy of each sensor for all the 13 activities for DTs with sampling widow size indicated in Table 5.5. In this figure, it is noticeable that the right hip sensor has higher classification accuracy for most of the activities. However, in

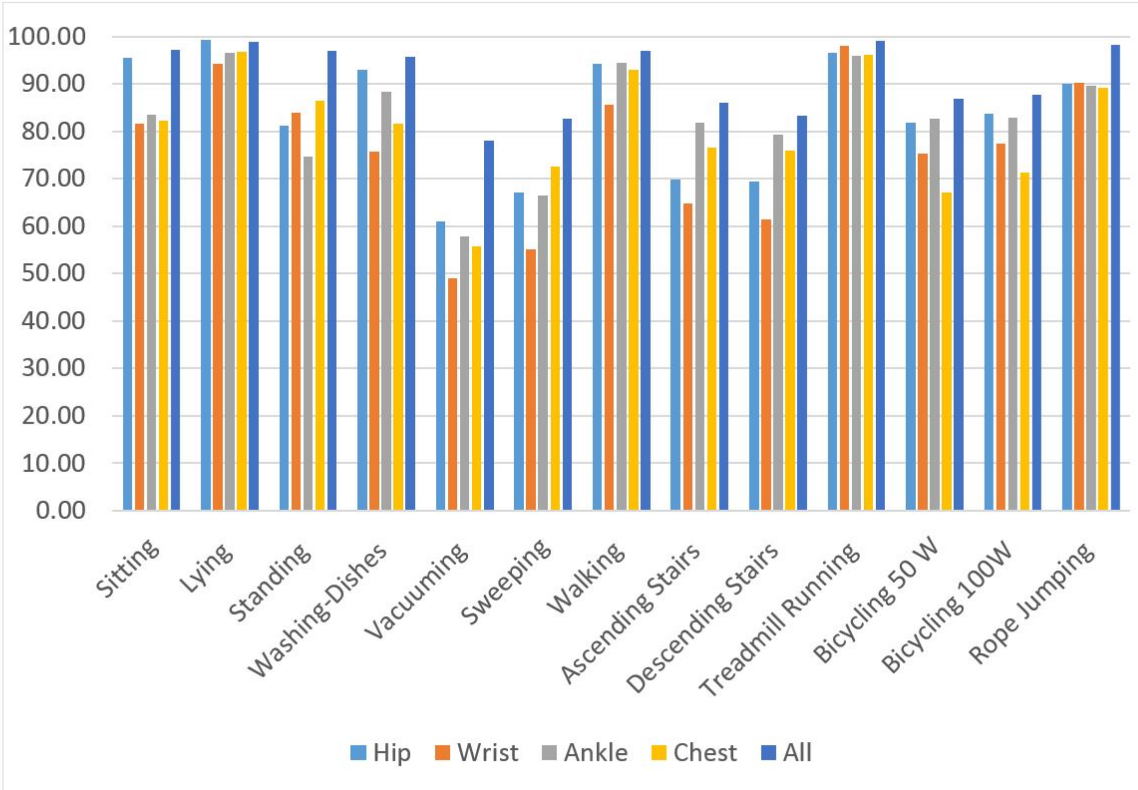


Figure 5.7: Using *Bench Mark* dataset, DTs accuracy of each sensor and all sensors together for all the 13 activities with sampling widow size indicated in Table 5.5.

activities depending on feet movements (i.e. walking, ascending and descending stairs and bicycling 50W) the left ankle sensor has the highest accuracy.

5.5 Conclusion

This work has considered the recognition of a small set of activities based on accelerometer data from an individual with Parkinson's disease. A novel feature set is considered and a *Bench Mark* data set of daily household activities is used to provide a comparison. Since accelerometers are primarily in a $1g$ environment, it is relatively easy to compute the angle between a sensor worn on the individual's trunk and the gravity trajectory. This, together with the dot product of successive acceleration vectors, provides significant features for recognising a person's activities using accelerometry.

A Decision Trees classification method with a sliding window of size nearly one second was shown to be significantly better than a Naïve Bayes approach. This study showed that the inclusion of data from additional sensors placed on the person's wrist, ankle and chest improves the classification process and will lead to enhancing the results, particularly for the classification of walking activities.

Projecting of accelerometer data onto a $1g$ sphere helps to illustrate the importance of this approach and the problems of sensor alignment. A multi-levels classification system that exploits several algorithms with different window sizes will be exploited in future work to increase recognition accuracy.

In addition, the detection and correction of data of misaligned sensor will be considered in future work. It is clear that better knowledge of the underlying cause of the data will lead to the higher validity of information transmitted at a lower rate. This is particularly important in the case of long term ambulatory wearable sensors where data must be transmitted from the individual to a base station through a low energy channel at a low bit rate.

Chapter 6

Dynamic System Method for Classification of Human Activities

6.1 Introduction

One of the basic machine learning tasks is classification. Classical classification algorithms depend on feature vectors. Through the past two decades, such algorithms have been expanded to classify increasingly complex data, e.g. time-series data [110, 133]. The sampling of time-series data could be irregular and/or sparse in several real-world applications [110], which creates a challenge for time-series classification. However, in such applications, the generation processes of data can be well understood and mechanical models representing for the data structure can be developed in a dynamic systems' form. Such mechanical models' usage in the classification of time-series would permit incorporating the domain experts' knowledge.

In this setting, a human is a physical object moving in a physical space in ways which can be represented by ordinary differential equations. In other words, the human can be seen as a dynamical system. This means that acceleration data, which is time-series data, collected by wearable sensors could be considered as observations of the underlying human dynamical system and the classification of observed dynamical systems would become the machine learning task.

This chapter will present an exploiting and validating of dynamical systems modelling method for the classification of human daily living activities. This method is Recursive Least Squares with Forgetting factor (RLSF) which was described in section 4.6. To our knowledge, this is the first work that exploited such a method for the classification of human activities from accelerometer sensor data. The *Bridge* and the *Bench Mark* data sets illustrated in section 5.2 were again used in this work.

6.2 Methods used

The work presented in this chapter was to investigate the application of the RLSF algorithm (described in section 4.6) for the classification of human activities. By exploiting the RLS algorithm, two classification methods were proposed: The Prediction Measuring method (PM) and the Model Matching method (MM), which will be both described in the following subsections.

The main idea of our methods is to identify a model that predicts the same output, or as close as possible, as the original system. These approaches were developed in order to improve the classification accuracy of data collected by only one wearable sensor and reduce training data used for creating a classification model.

6.2.1 Prediction Measuring (PM) method for classification of human activities

The main idea of this approach is to perform classification by comparing predicted and actual data samples. Figure 6.1 depicts a graphical model for the proposed PM classification system. As shown in the figure, the first step is the input of sensor data followed by the pre-processing step which could imply down-sampling or oversampling the data, and/or any essential preparation of data before processing.

To choose the best data sampling rate, several experiments were performed by using the data in its original sample rate and by down-sampling it to 75%, 50% and 25%. Two methods were used for down-sampling: first 'resample' a MATLAB function that detrends and interpolates the data, and second a 'picking method', which involves picking one two or four data samples from every four data points depending on the down-sampling percentage.

The picking method achieved the best classification results. Thus, in the experiments presented in this thesis, the data frequency rate of *Bench Mark* data set was down-sampled from 204 Hz to 51 Hz by picking every fourth sample which makes up 25% of the data. In the third step, the data is partitioned into training data and testing data. To determine the best segment size of training data (of *Bench Mark* data set) that can be used to create the system identification model for each activity in the data set, a range of window sizes was evaluated, that is 51, 102, 255, 510, 765 and 1020 data samples.

These window sizes represented approximately 1, 2, 5, 10, 15, and 20 seconds of data respectively. The test data that was used for validating the model in the rest of the data after selecting the training set. For example, if the total activity recorded time for an activity is 120 seconds and the training set is for 15 seconds, the testing set will be 105 seconds which corresponds to 12.5% for the training set and 87.5% for the testing set.

After data partitioning, a model m_i (where $i = 1$ to c, and c is the number of classes in the data set) will be created for each class (or labelled human activity) using RLSF algorithm which described in section 4.6. Algorithm 1 illustrates the steps of model creation, where $\hat{\theta}(n)$ is the model parameter vector, n the time instance, T the window size, $y(n)$ the output measured at time (n), λ the forgetting factor and $\varphi(n)$ a vector of input values.

Algorithm 1: Create the model m_i using RLSF

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initialization: Set $\lambda = 0.99,\ \hat{\theta}(0)\ and\ P(0)$;
for $n = 1$ *to* T **do**
  At time step n, measure current output $y(n)$;
  Recall past y's to form $\varphi(n)$;
  Apply RLSF algorithm for $\hat{\theta}(n)\ and\ P(n)$;
  Update $\hat{\theta}(n) \rightarrow \hat{\theta}(n-1)\ and\ P(n) \rightarrow P(n-1)$;
end
The model $m_i = \hat{\theta}$

A number of structures have been tried for the algorithm input vector $\varphi(n)$. Table 6.1 lists these structures in descending order according to the classification accuracy results acquired when they used.

Table 6.1: Structures tried for the algorithm input vector $\varphi(n)$. X, Y and Z are the axes of the accelerometer sensor.

Order	Description	φ structure
1st	One previous data point squared.	$[X_{n-1}^2\ Y_{n-1}^2\ Z_{n-1}^2]$
2nd	One previous data point.	$[X_{n-1}\ Y_{n-1}\ Z_{n-1}]$
3rd	One previous data point squared and not squared.	$[X_{n-1}\ Y_{n-1}\ Z_{n-1}\ X_{n-1}^2\ Y_{n-1}^2\ Z_{n-1}^2]$
4th	Two previous data points.	$[X_{n-1}\ Y_{n-1}\ Z_{n-1}\ X_{n-2}\ Y_{n-2}\ Z_{n-2}]$
5th	Two previous data points, the first one squared.	$[X_{n-1}\ Y_{n-1}\ Z_{n-1}\ X_{n-2}\ Y_{n-2}\ Z_{n-2}\ X_{n-1}^2\ Y_{n-1}^2\ Z_{n-1}^2]$

The testing set of data is divided into 1, 2, or 5 seconds 50% sliding windows of data points. Each model m_i will apply to each sliding window to predict the data points of the window. The final step of the PM method is measuring the Euclidean distance between the predicted data point of each class model and the actual data points of the sliding window. The Euclidean distance (d_E) is calculated as in equation 6.1 [133]. The mean of the Euclidean distances for each class model will be calculated and the class model that achieves the smallest distance will be the class of that window.

Figure 6.2 shows the functionality of the new data point prediction, distance measuring and best class selection.

$$d_E = \sqrt{\sum_{n=1}^{T} (\hat{y}_n - y_n)^2} \tag{6.1}$$

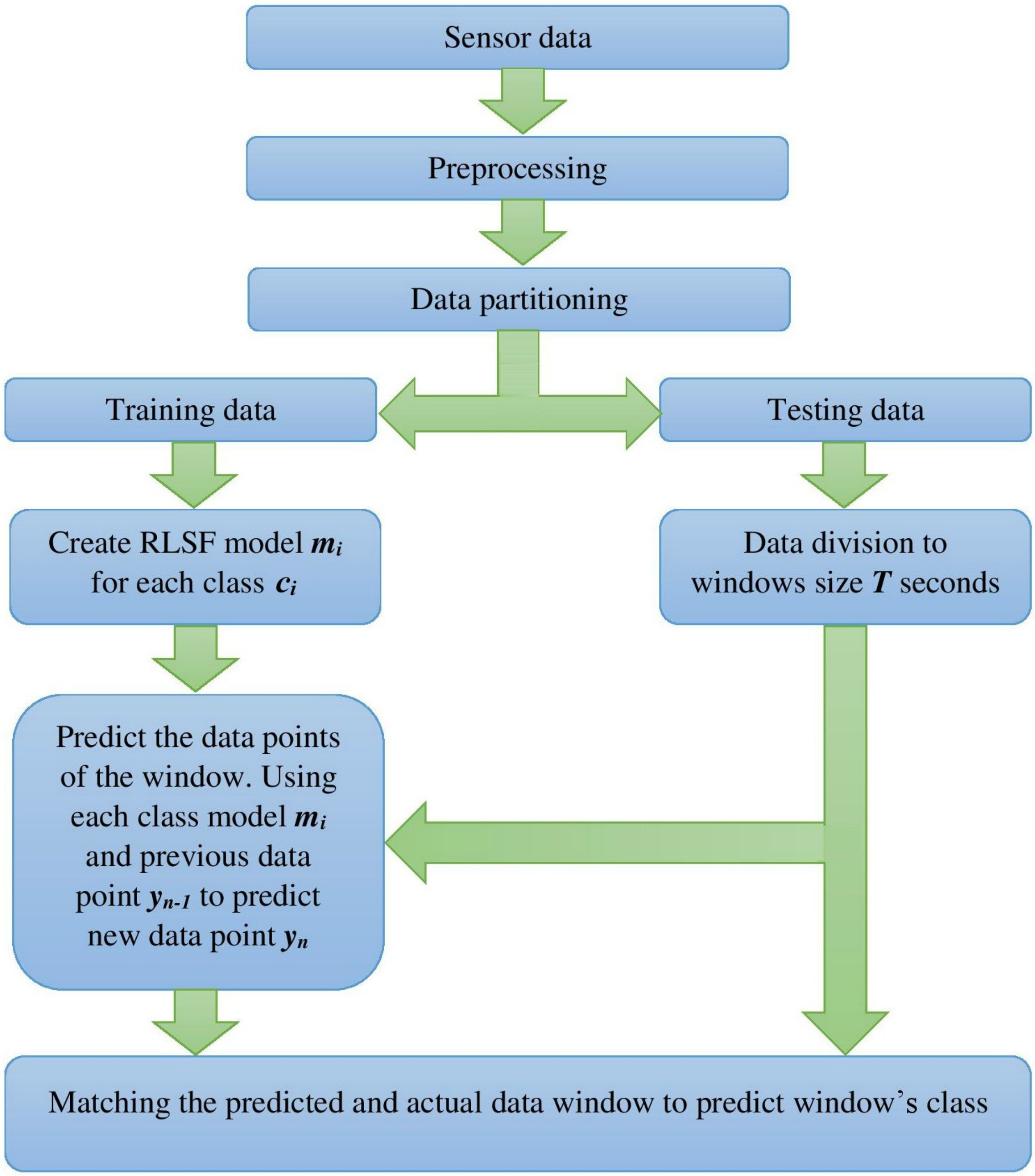

Figure 6.1: Graphical model for the proposed PM classification training and validating processes. The method validation is further detailed in figure 6.2 and in the text.

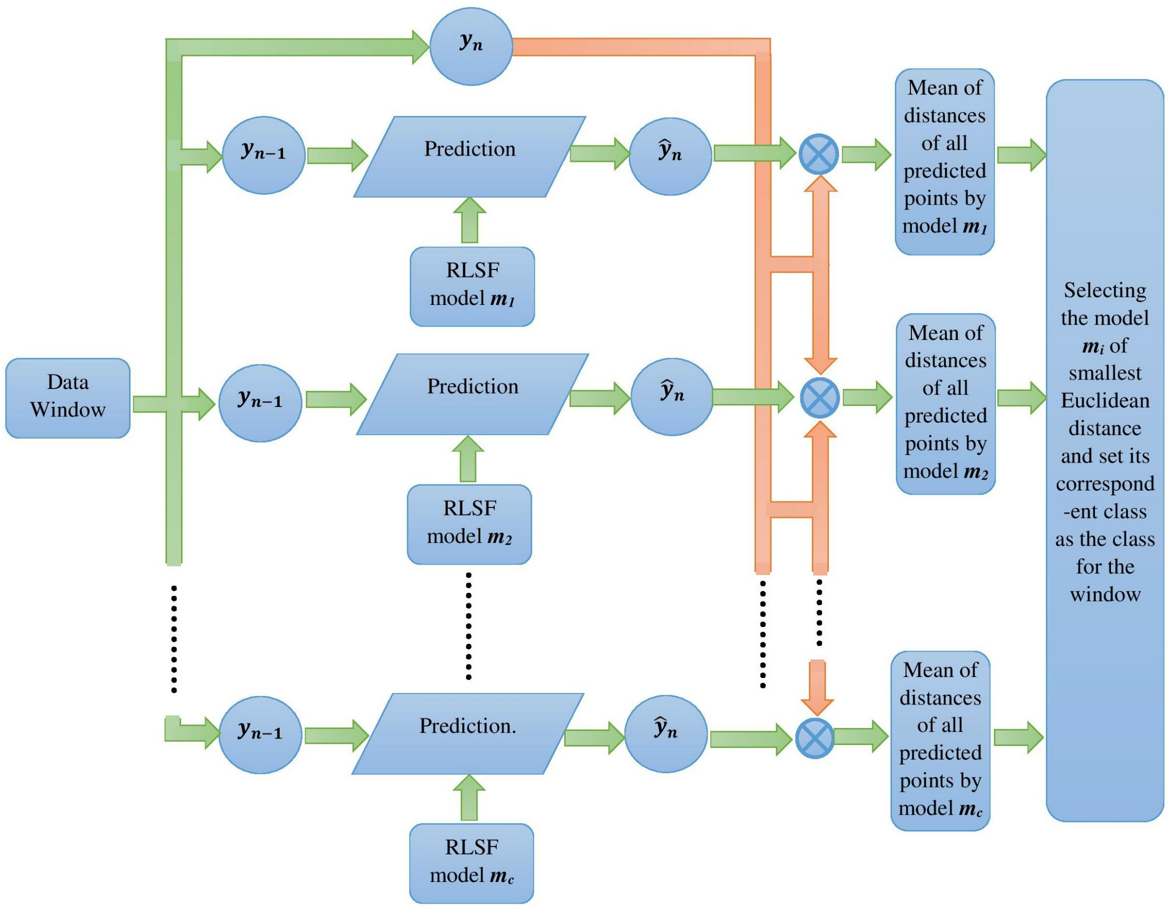

Figure 6.2: Graphical model for PM method new data point prediction and distance measuring. Each model m_i predicts the next data point given data so far. The most accurate prediction based on the Euclidean distance to the actual data point is chosen as the best model for that window.

6.2.2 Model Matching (MM) method for classification of human activities

This approach has the main idea to create a reference model using training data, then create another model using testing data and then compare the models. Figure 6.3 depicts a graphical model for the proposed MM classification system. As shown in the figure, all the steps of this method, except the penultimate and final steps, are the same as the steps of PM method that described in section 6.2.1. The penultimate step includes using of RLSF to create a model m_g for each sliding window using testing data.

In the final step, a comparison will apply between the model m_g and each of the models m_i that created using training data. For comparison, the Euclidean distance will be calculated between the model m_g and each of the models m_i. The data class that related to the model m_i that achieved smallest distance with model m_g will be set as the class for the window.

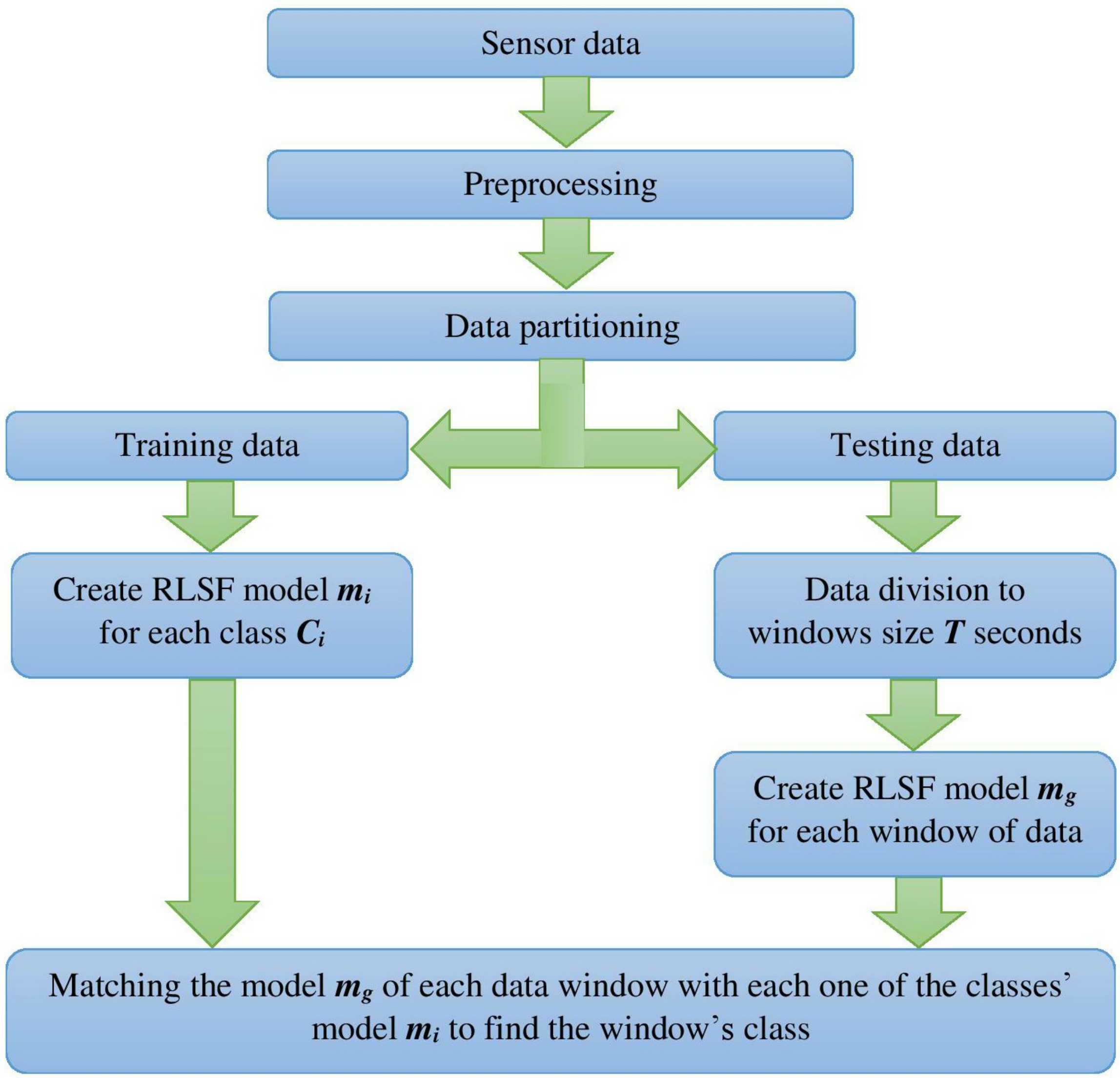

Figure 6.3: Graphical model for the proposed MM classification system.

6.3 Results obtained for classification of ADL by the proposed methods

The PM and MM methods were applied on the *Bench Mark* data set for each participant separately and the mean of the accuracy of all participants was calculated and presented for each experiment in this section. This is because when applying these proposed methods on the whole data set of 19 participants a low classification accuracy was noticed. This might be due that these methods are very dedicated to recognising each individual's data alone. Due to this, it is difficult to compare the proposed methods' classification results with state-of-art methods results in the literature.

However, for comparison purposes, three conventional methods (DTs, NB and kNN) were applied on the *Bench Mark* data set in the same way as applied PM and MM methods. For the proposed PM and MM methods, the 15 seconds training data and 5 seconds sliding window of testing data were used in all experiment which their results are presented in this section, and the forgetting factor was set to $\lambda = 0.95$. These settings achieved the best classification accuracy among other settings. As mentioned in section 6.2.1, a number of input structures to the algorithm were investigated. The first structure (will refer to this structure as 'Squared') and the second structure (will refer to it as 'Not-squared') shown in table 6.1 gave better classification accuracy than the others. Just these two structures were used in the results presented in this section.

Figure 6.4 depicts a chart of comparison of classification sensitivities for both approaches PM and MM in both structures Squared and Not-squared. The results presented in this chart are the mean of the results obtained from applying the proposed classification methods PM and MM on the hip sensor of *Bench Mark* data set 19 participants individually.

From the results presented in figure 6.4, it is clear that the PM method in Square structure achieved the best classification accuracy while the MM method in Not-squared

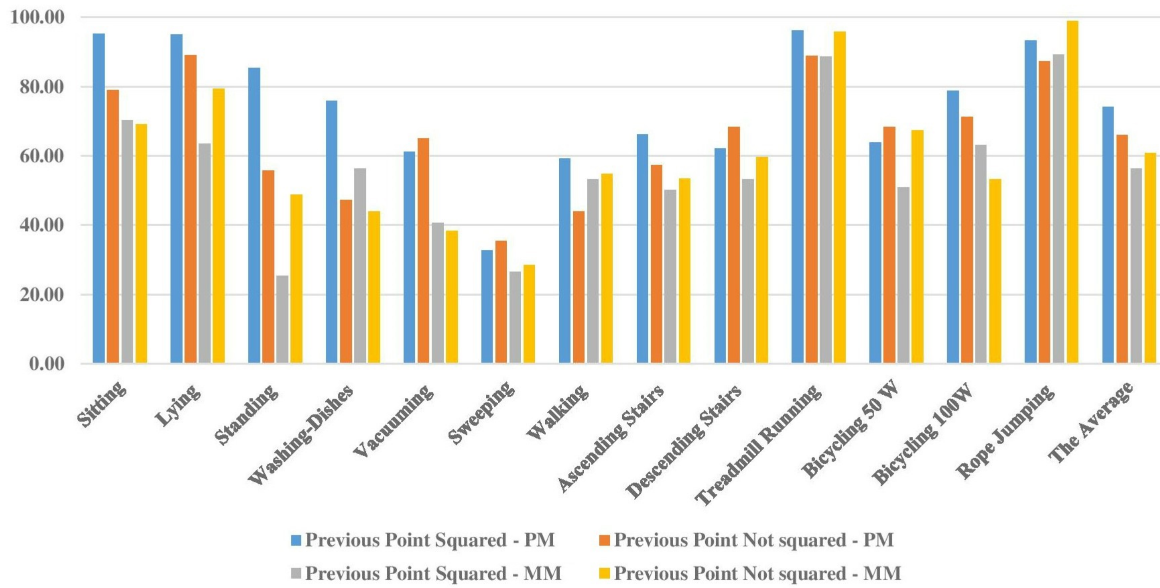

Figure 6.4: Comparing the hip sensor sensitivities results for both approaches PM and MM in both structures Squared and Not-squared.

structure gave a slightly better result than the Squared MM. The overall classification accuracy of the PM Squared is (71%), the MM Squared is (56%), the PM Not-squared is (61%) and the MM Not squared is (59%).

An experiment was performed to find the best location to place the wearable sensor on the human body. Figures 6.5 and 6.6 depict a comparison between classification sensitivities results of PM Squared method and MM Squared method respectively for human activities data of hip, wrist, ankle and chest sensors.

The overall classification accuracy of the PM method for the hip sensor is (71%), wrist sensor (57%), ankle sensor (57%) and chest sensor (68%). The total classification accuracy of the MM method for the hip sensor is (56%), wrist sensor (45%), ankle sensor (43%) and chest sensor (49%).

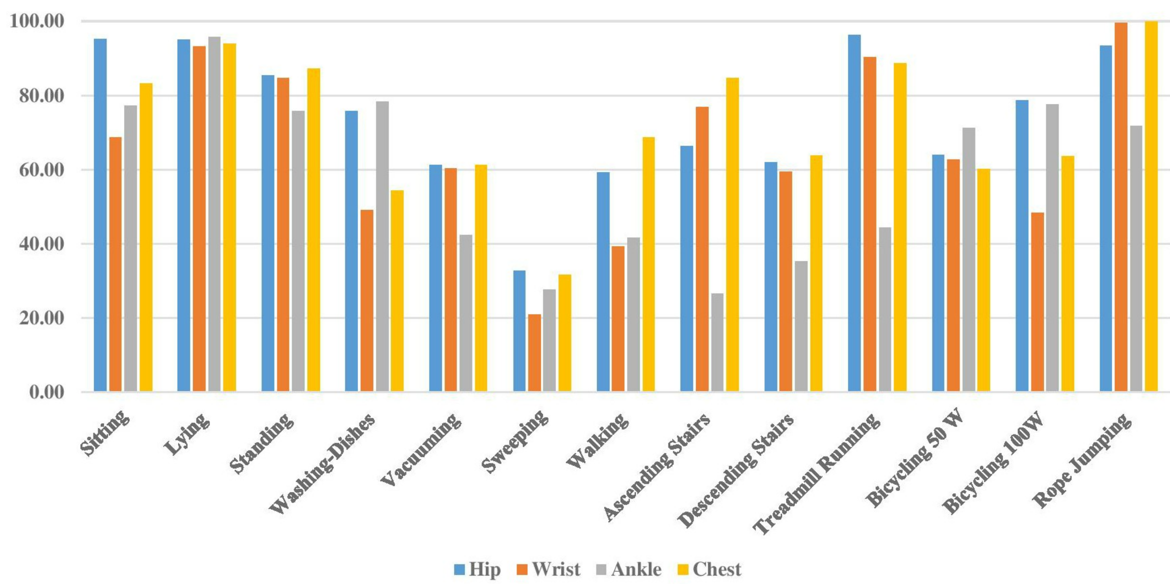

Figure 6.5: Classification sensitivities of activities for all participants separated using Squared one previous data point PM method.

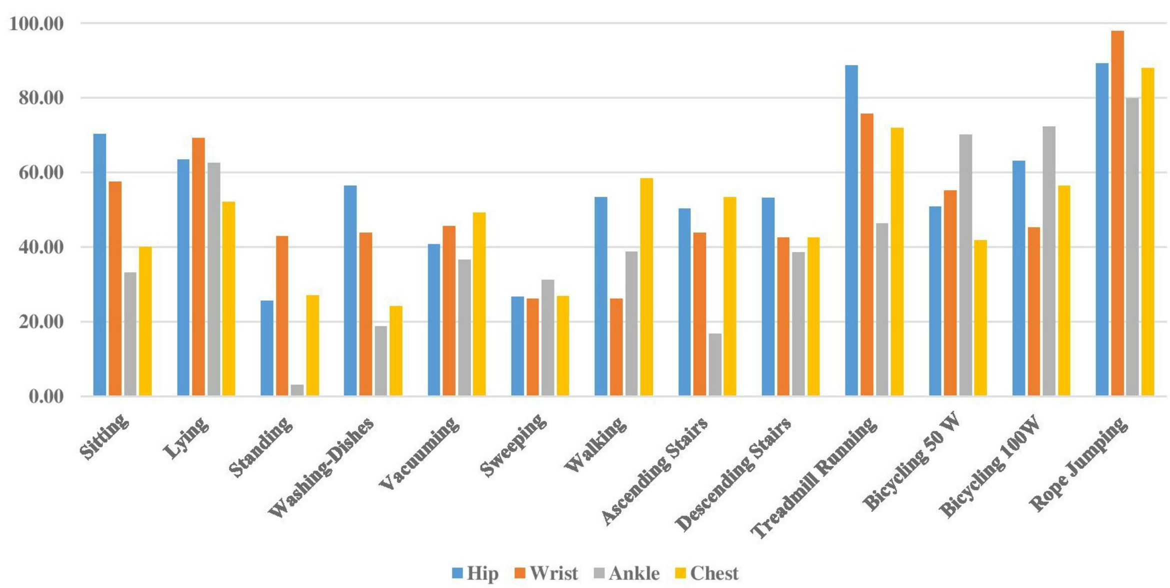

Figure 6.6: Classification sensitivities of activities for all participants separated using Squared one previous data point MM method.

Figure 6.7 shows the results of classification sensitivities of the proposed PM Squared method and three conventional methods that are DTs, NB and kNN. All methods were applied on the hip sensor of *Bench Mark* data set. Only the proposed features in

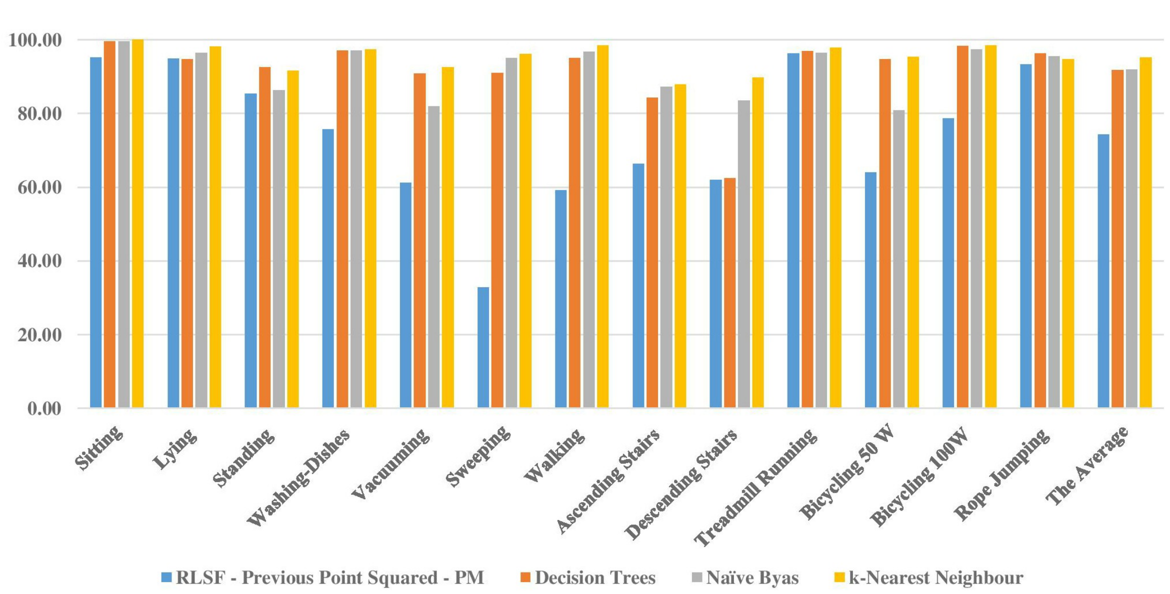

Figure 6.7: Comparing classification sensitivities of proposed PM method with DTs, NB and kNN.

chapter 5 were used with conventional methods.

For the comparison, the conventional methods were applied to the participant separately in the same way as the proposed method, the data set partitioned into 70% training set and 30% testing set, and 5 seconds sliding window for feature extracting. as mentioned above the PM proposed method classification accuracy was (71%), while the accuracy of DT was (94%), NB was (93%) and kNN was (96%).The *Mr T Bridge* data set, that collected from a participant with Parkinson's in his home, was used for the purpose of validating the proposed method and for comparison with the DTs method.

Table 6.2 shows the classification accuracy of the DTs algorithms using the method proposed in chapter 5 and the classification accuracy of the proposed PM method. The classification accuracy results show that the PM method performed low accuracy comparing to the DTs algorithm. However, the results demonstrate that a model-based classification mechanism is viable.

Table 6.2: Classification accuracy (in per cent) for DTs and PM using *Mr T Bridge* data set. The results marked by bold indicate the higher classification accuracy.

Activities	**DTs**	**PM**
Sitting	**99.63**	89.04
Standing	**98.35**	53.45
Sit to Stand	68.75	**87.60**
Stand to Sit	**66.67**	16.62
Walking	**90.91**	17.48
Stairs-up	**87.50**	70.06
Stairs-down	**66.67**	23.28
Turning	50.00	**100.00**
Overall Accuracy	**78.56**	57.19

6.3.1 Analysis of results and discussion

The space of dynamical systems relating to inertial measurement is highly nonlinear but is often analysis with linear features. For example, rotational measurements are linear when measured by a gyroscope but depend on the square of the acceleration measurement when measured with an accelerometer. This can also be seen from the results presented in figure 6.4, where the PM method with the 'Squared' structure (which is nonlinear) outperformed the PM method with the 'Not-squared' structure (which is linear). These non-linearity characteristics can be considered by appropriate selection of coordinates or appropriate representation in higher dimensional spaces. Although true in this case, classifiers with linear features are widely used where the underlying system can be considered linear. In addition, the PM method with the 'Squared' structure achieved better classification result than the MM method, as shown in the figure.

The main reason for the big difference in classification accuracy between the two methods could be the method used to measure the distance between the trained model m_i and the test model m_g created by the MM method. The used Euclidean distance is a simple way of matching the two models.

Thus, there is a need to develop a function for measuring the distance between the models to enhance the classification accuracy of the method. The result shown in figures 6.5 and 6.6 highlights that the PM method outperform the MM method. Moreover, these results show that the best location of the wearable sensor is on the hip and the chest, confirming the observation of King et al. [27].

The PM method classification accuracy of the hip sensor data is (71%) and the chest sensor data is (68%) which quite higher than the results of other sensors for both methods PM and MM. This means that the proposed methods achieve better classifying accuracy using data of sensors located on the human trunk comparing to sensors located on the limbs. Because limbs have more freedom to move than the trunk, the sensors placed on the wrist and ankle can acquire higher acceleration and larger variability data than sensors placed on the hip and chest. This variability and the saturation of the acceleration measurement could mean that these methods did not perform as well with such acceleration data.

However, the figures show that the classification results of hip, chest and wrist sensors are good for sedentary (sitting, lying and standing), and high speed (running, bicycling and rope jumping) activities.

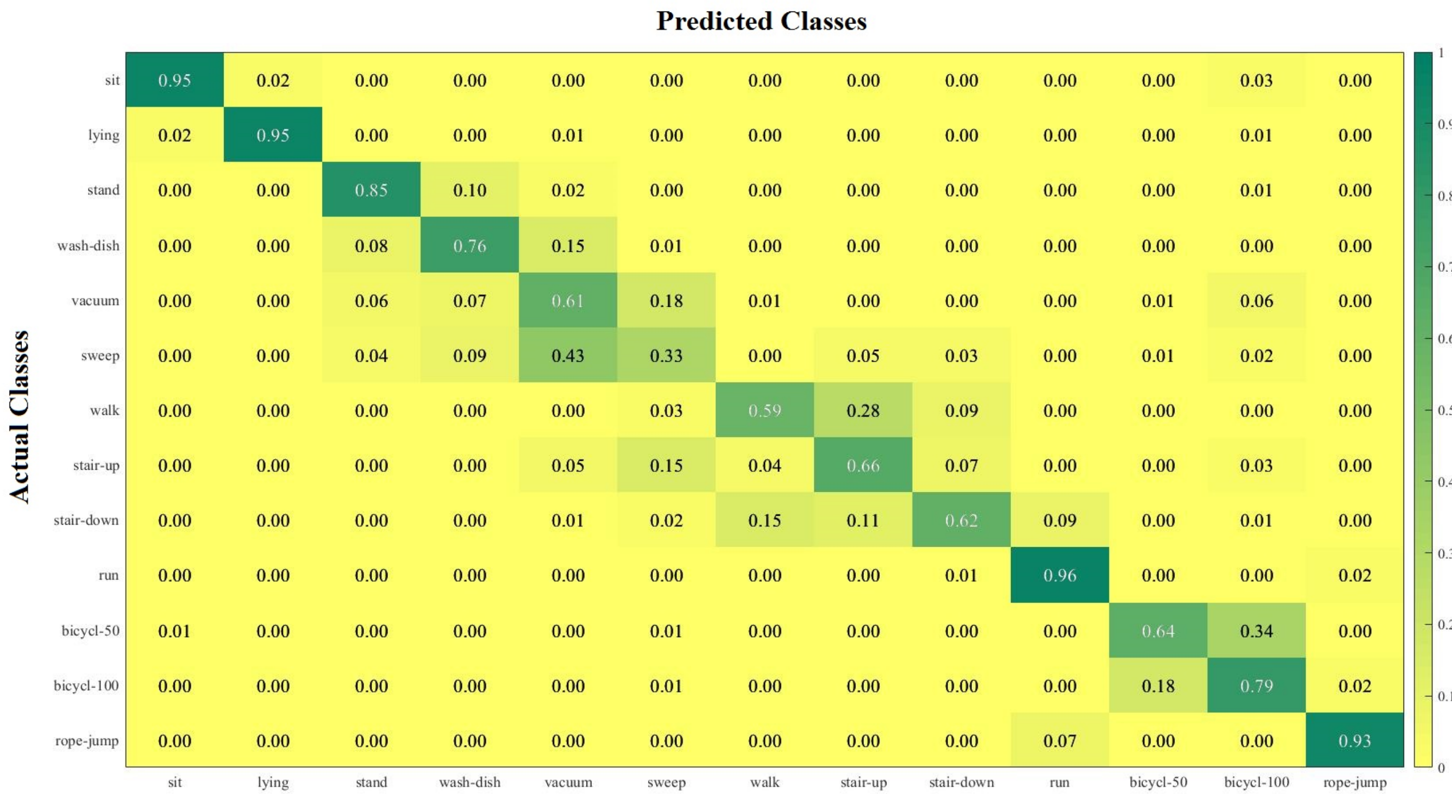

Figure 6.8: Confusion matrix in percentage of PM method applied on hip sensor data of 19 participants of the *Bench Mark* data set.

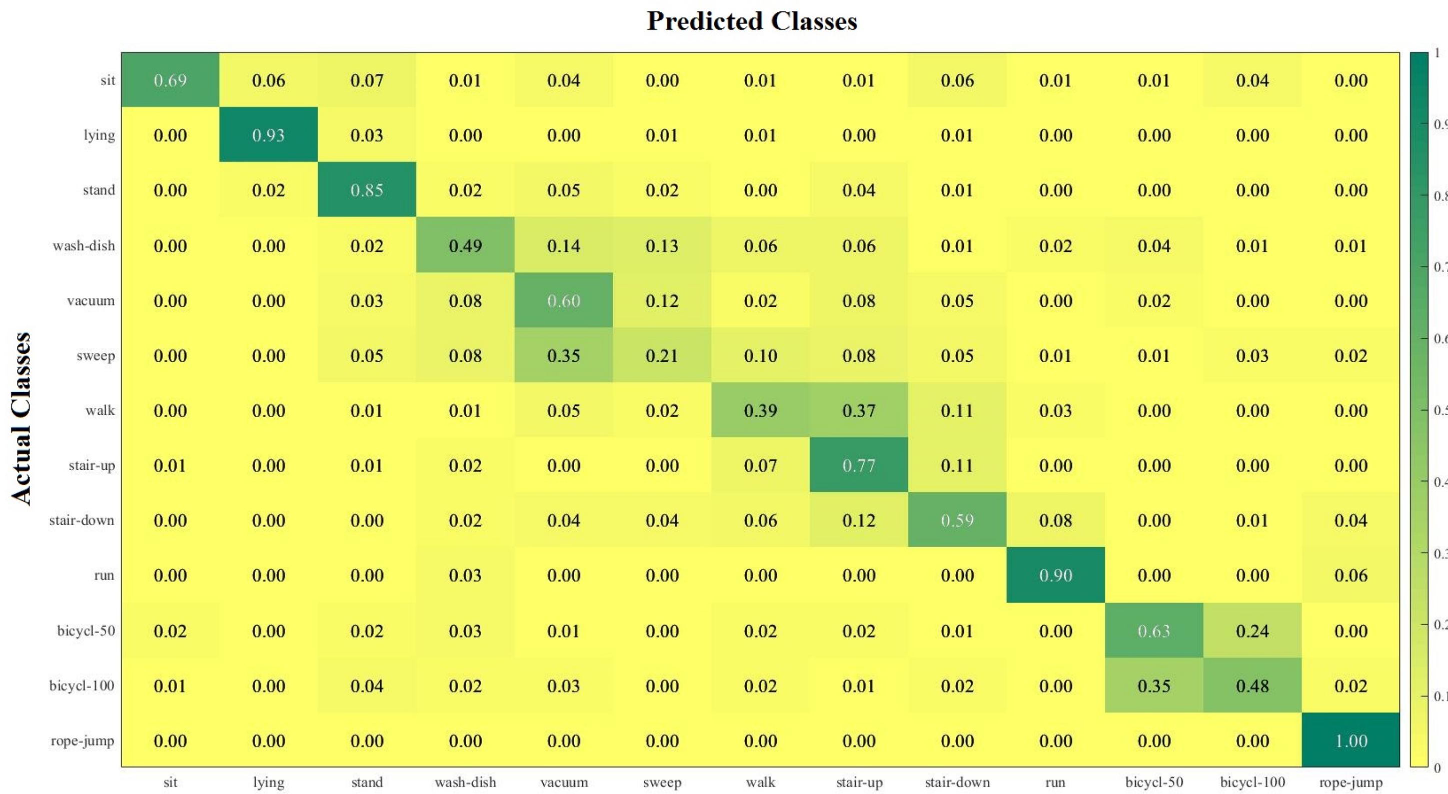

Figure 6.9: Confusion matrix in percentage of PM method applied on wrist sensor data of 19 participants of the *Bench Mark* data set.

Figures 6.8 and 6.9 depict the confusion matrix of the PM method applied on the hip and wrist sensor respectively. It is clear that the classification method confused between household activities (vacuuming and sweeping), ambulation activities (walking, stair-up and stair-down) and cycling activities (bicycl-50 and bicycl-100). Because the nature of performing each set of these activities is looking similar, each of those activities models will predict similar data point to the other points estimated by the other models. Therefore, the proposed classification method will miss-classify these specific activities. Figure 6.7 depicts a comparison between the PM method in 'Squared' structure and the conventional classification methods (DTs, NB and kNN) using *Bench Mark* data set and Table 6.2 shows a comparison between the same proposed method and DTs using *Bridge* data set.

Both the figure and the table show that the conventional methods outperform the results of the PM method. This result is not unexpected as full structures of PM are yet to be explored. Furthermore, there is an issue that made the PM and MM methods yield low classification accuracy results comparing to other methods is the approach used to measure the distance between the predicted and the actual data points. These methods depend on this measurement to classify the data.

The reason for choosing the Euclidean distance to achieve this task was to reduce the complexity of the classification method. Thus, to increase the classification accuracy for both proposed methods, it is suggested to develop a special function that can measure this distance rather than the Euclidean distance. The high classification accuracy results of the DTs, NB, kNN algorithms achieved here comparing to their results in chapter 5 section 5.4.1 are because they applied to each participant's data separately from the rest of the participants.

An additional benefit when considering this approach is to reduce the algorithm complexity. Both PM and MM methods have a training time complexity of $O(n)$, where n is the size of training data. This is a significant achievement comparing to the training time complexity of the conventional algorithms such as decision trees $O(m, n^2)$, Naive Bayes $O(m, n)$ and kNN $O(n^2)$, where m is the size of the training data and n is the number of attributes [134, 135, 136].

6.4 Conclusion

This work has investigated the structure and performance of a classification method using a system identification algorithm to build a dynamical model of the underlying process. The idea is evaluated in the classification of human activities of daily living using wearable sensor data.

Two novel methods were proposed for achieving the classification purpose. The two methods are called *Prediction Measuring* (PM) and *Model Matching* (MM). Both of the methods use the recursive least square algorithm with a forgetting factor to identify a model for each activity using about 15% of the raw data. The identifying models were applied on the rest of the data for classification purposes using a Euclidean distance to measure the predictions. Both approaches were applied to a single accelerometer of *Bench Mark* data set which includes data of 19 participants performed 13 human daily activities, and *Bridge* data set of a person with Parkinson's disease performed a small set of activities.

The proposed PM method achieves good classification accuracy comparing to the MM method which acquired low classification accuracy. The results were compared to the results of conventional classification algorithms applied to the same data sets using the features proposed in chapter 5.

The Decision Tree, Naive Bayes and k-Nearest Neighbour algorithms achieved high classification accuracy comparing to PM and MM methods. The reason for this is likely that the misclassification of some activities that tended to have a similar pattern, that are household activities (washing dishes, vacuuming and sweeping) and walking activities (walking, ascending stairs and descending stairs).

Another main reason is the approach used to measure the model prediction in both methods which is the Euclidean distance. This is particularly true of MM method where data variance and model quality are determining factors. This raise the need to think about using an alternative method for measuring distance.

This could be achieved by taking into account the geometry of the space defined by orientations of an accelerometer in earth's gravity and attempting to compute the geodesic distances on the surface of $1g$ sphere rather than a Euclidean distance. This would necessitate projecting data onto this sphere but keeping the distance above the sphere as an indication of the movement. Additional research could be done by constraining the model to reflect simple system dynamics.

Furthermore, the acquired results showed the non-linearity of the system as the results of squaring the data points in the creation of the model and in the prediction of the new data points were best than when not squaring them. In addition, the results showed that the best location for the sensor on the human body is on the hip then on the chest. This could be because of the nature of these methods, as a time series methods, that predict the new data point according to the model's previous knowledge. The model's knowledge could be better in the case of sensors placed on the trunk rather than the sensors worn on the limbs as they have more freedom movement.

Finally, the proposed method validated the usefulness of using the system identification approaches in the classification of human activities and the ability to classify most of the basic activities with high accuracy using the hip sensor only.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

The aim of the research conducted for this thesis was to find and validate a method to classify human activities from data collected by wearable non-invasive sensors, which provide an accurate and reliable assessment for healthcare and individual well being. To address this aim, three research questions were investigated. This section summarises the conclusions of the research related to each of these questions.

7.1.1 Extract relevant features for human activity classification

Chapter 5 presented the work of considering the classification of human activities of daily living based on a wearable accelerometer sensor data. Most of the previous researches in the literature used a large set of features to classify the data which result in increasing the method complexity and the execution time.

The main aim of this work was to find useful features that lead to achieving good classification accuracy without increasing the complexity of the classification procedure. To achieve this, the angle between a sensor worn on the person's trunk and the gravity trajectory was considered.

It is easy to compute such an angle since the accelerometer is primarily in a $1g$ environment. This angle together with the dot product of successive acceleration vectors provides significant features for classifying an individual's activities using accelerometry. A data set collected from an individual with Parkinson's disease in his own home performed 8 activities of daily living that was used to investigate these features. A Decision Tree classification method with a sliding window of size nearly one second was achieved classification accuracy (79%) and a Naive Bayes method achieved (85%).

A *Bench Mark* data set of 19 participants performing 13 daily household activities was used to provide a comparison with a state-of-art method. The proposed method with Decision Tree Using four sensors data (52 features were extracted) achieved an overall classification accuracy (91.38%) comparing to the state-of-art hierarchical method which used four sensors data (152 features were used) that achieved (89.6%) overall accuracy. This result verifies the usefulness of the proposed method to project accelerometer data onto a 1g sphere helps to identify the proposed features, illustrates the importance of this approach and the problems of sensor alignment.

7.1.2 Exploiting of systems identification approach in classification of accelerometer data

Chapter 6 demonstrated the work of considering the human movement as a dynamic system and investigating one of the system's identification approaches to recognise human activities. Two methods *Prediction Measuring* (PM) and *Model Matching* (MM) were proposed for this purpose. Both of the methods use the Recursive Least Square algorithm with a forgetting factor to identify a model for each class using about (15%) of the data set.

The model should apply to the rest of the data set to perform the classification process. The PM method achieved good classification accuracy (71%) comparing to the MM method which acquired (59%). Although the classification accuracy results of the newly proposed methods were not as high as the conventional methods, the PM method achieved good results using about (50%) of data compared to the other methods that used (70%) of data for training. The fewer data for training result in reduced calculations and low use of power and memory. The main reason for the low results of proposed methods is the approach used to measure the distance between the predicted and actual data points which is the Euclidean distance.

However, by using this measuring approach, the proposed method can classify the simple activities in high accuracy and can also differentiate between different sets of activities (i.e. sedentary, low speed and high speed) in high accuracy. The MM method possibly demonstrates the problem of model over-fitting. This implies that there is either insufficient data for a model or there is too much variance in the sensor data.

7.1.3 Validating the best location for the wearable sensor on the human body

The works presented in chapter 5 and chapter 6 used the proposed methods to investigate the best location to wear the sensor on the body to collect distinctive measurements of human activities. All the acquired results showed that the hip sensor was linked with the best classification accuracy comparing to the other locations (wrist, ankle and chest).

However, hip sensor can recognise the simple ADL in high accuracy but it is useful to consider another sensor, such as a wrist sensor, to recognise the more detailed activities, for example, reading, writing, using phone, cooking, etc. In addition, using multiple sensors can increase classification accuracy. Therefore, depending on the application and the needed level of accuracy could make the choice between wearing a single sensor or multiple sensors on different body locations

7.2 Future work

According to the results presented in chapter 5, that showed the outperform of each of the classification algorithms in recognising a particular set of activities with high accuracy and to increase the classification accuracy of the approach proposed in chapter 5, it is feasible to investigate a multi-level classification system that uses a number of algorithms with different data window sizes.

The system could classify the activities in the first level according to their activity group (i.e sedentary, moderate and vigorous). Then performs the classification in more detail.

It is good to present the data in different visualising forms to have a better understanding of the underlying cause of the data which will lead to the higher validity of information transmitted at a lower rate. This is particularly important in the case of long term ambulatory wearable sensors where data must be transmitted from the individual to a base station through a low energy channel at a low bit rate.

It is important to investigate a new approach to measure the distance between the predicted and actual data point for *Prediction Measuring* (PM) method and to matching the training and validating models for *Model Matching* (MM) method. This may be achieved by considering some features of the space to compute more accurate distance. The PM and MM methods could run data forward to reduce dependency on the slid-window, which will result in reducing of the size of processed data. A need to collect accelerometer data for long-term uses; to examine the PM and MM methods model's ability to identify the changes in person's activity over time, which may due to a health issue that needs to make the person aware about it. This could be achieved by performing a routine comparison between the new updated model and the old models.

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