SUBJECT-DEPENDENT PHYSICAL ACTIVITY RECOGNITION USING SINGLE SENSOR ACCELEROMETER

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This dissertation is submitted for the degree of Doctor of Philosophy

October 2014

Dedication

To my beloved parents,

and professors.

ABSTRACT

Rapid advancement in the field of Artificial Intelligence, to be more specific in Machine Learning and Nanotechnology, strengthens hopes to better understand human mind. Ubiquitous Computing helped in the creation of intelligent environments pervaded by these visible and invisible devices, which are affecting and improving all aspects of human life. So, as a consequence, smart environments work on the behalf of humans for ease of comfort. The ultimate goal is to monitor humans without any awareness by them of computer interaction. The understanding of how humans will interact and make use of such systems is however largely unresolved and often not addressed collectively from both scientific and medical aspects in current research. A key to understanding such systems and their use is the observation that humans implicitly interact with their environment. The task of making this context information available to components in computer systems has become a prerequisite to move forward in human-computer interaction. Context awareness or more specifically how to create applications that are context aware is a central issue to Ubiquitous Computing research. Such research raises questions on context acquisition, context representation, distribution and abstraction, as well as programming paradigms, development support, and implications on human-computer interaction in general.

The aim of this thesis is to develop part of a ubiquitous care system to monitor elderly basic daily life activities; stand, sit, walk, lay and transitional activities. This thesis investigates the use of a wearable sensor (tri-axial accelerometer) to develop and evaluate the activity classification scheme with reliable accuracy in the real-world situations. The recognition of these activities is challenging because activities with similar posture are hard to discriminate (e.g. stand and sit). Moreover, this high similarity among activities is not uniform throughout the whole dataset which raises the question of how much training data would be required. Furthermore, the activity classification schemes proposed in literature are typically subject-independent; however there is lack of evidence that such subject-independent schemes have been successfully validated with elderly in uncontrolled situations.

Firstly, a detailed accelerometer sensor's data analysis was conducted using different literature highlighted features. The analysis indicated that each physical activity may exhibit inter-subject variability, depending upon subjects' physical characteristics, weight, height, health status etc., and intra-subject variability due to change in physical conditions, environment, and situations which is a major drawback. Therefore, by applying different threshold-based activity recognition techniques and clustering algorithms we end up with different accuracy results (as mentioned in literature). In order to address the data variability within any activity, a simple mathematical model using statistical parameters was implemented. The proposed model not only confirms the classified activity with 95% confidence but is also capable of calibrating the statistical parameter, in case

of activity behaviour change. Unlike threshold-based techniques, the proposed activity recognition system employs a better mathematical model which is robust and classifies activities with consistent accuracy in real-time. The need of labelled activity data becomes crucial in long-term activity monitoring situations which is often impractical or impossible. In case of unlabelled data, usually traditional clustering algorithms were used in literature, which require careful data analysis as activity data is unlabelled. A semi-supervised clustering model is presented which, unlike traditional clustering algorithms, require less labelled data to train the classifier. Moreover, the feature extraction and computation was done in real-time. The core model for the clustering approach is a physical activity transition model which imitates different states of postures and transitions of human activity. A simple classifier based on k-Means was implemented to associate new observed activity data to the prior activity information as a result of the statistical model.

In order to validate the presented activity recognition system, two independent studies, one in a controlled laboratory environment and other in an uncontrolled real-world situation, was conducted with healthy and elderly participants respectively. The aim was to validate the recognition system accuracy in both environments. The accuracy achieved in the controlled environment with 7 healthy subjects was 93.8% and the accuracy achieved in uncontrolled environment with 30 elderly subjects was 90.8%. The indicated classification accuracy results reflect the correct recognition of stand, sit, walk and lay activities, where the transitions among these activities were considered as unclassified.

ACKNOWLEDGEMENTS

First of all, I humbly thanks to Almighty, who always shows his blessings in every moment of life by giving me strength, courage, patience and determination to achieve my goals.

I am obliged and sincerely thankful to my supervisor, Professor Roberto Bisiani, for giving me an opportunity to move into the world of research. He provided me continuous guidance, advice and motivation to get through this PhD. He has been always there whenever I need his support. I don't have those words to say thanks to him. However, I do feel to say him, "Prof! I wish I could do better".

I am very thankful to Dr. Davide Merico and Mr. Gabriele Rizzi for their educational and technical support in the early stages of my research studies. Their valuable feedback and discussion on my research was always helpful. I am also grateful to Professor Enza Messina to be my tutor in PhD programme.

The opportunity to work with research group; Human Movement Control and Movement Disorders, of exciting and enthusiastic people for research in Norway, I can never forget. Professor Jorunn L. Helbostad being a head of the research group and my co. supervisor provided me every possible help in order to conduct my research. I am so thankful to her kind support and without her probably I couldn't conclude my research work. Furthermore, I would like to say thanks to each member of the research group and especially Dr. Ather Nawaz with whom I had stimulating discussions about the research in general.

Lastly my parents and siblings, I have no words to express my deepest gratitude for their endless love, encouragement and prayers for me. My parents would be the happiest persons to see their efforts and sacrifices resulted in accomplishment of my PhD studies. I wish that I could utilize my knowledge and experience for the improvement of the society.

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1 INTRODUCTION

1.1 Motivation

Advancements in computing and communication systems combined with the development of micro-electromechanical systems (MEMS) are changing the way the physical world is understood. During the past decade, there has been an exceptional development of microelectronics and computer systems, enabling sensors and mobile devices with unprecedented capabilities. Their high computational power, small size, and low cost allow people to interact with the devices as part of their daily living. That was the genesis of *Ubiquitous Sensing*, an active research area with the main purpose of extracting knowledge from the data acquired by pervasive sensors (Perez et al. 2010). The task of making context information available to computer systems has become a prerequisite to move forward in the direction of human-computer interaction. Context awareness or more specifically how to create applications that are context aware is a central issue to Ubiquitous Computing research. Such research raises questions on context acquisition, context representation, distribution and abstraction, as well as programming paradigms, development support, and implications on human-computer interaction in general.

Recent and current research is moving towards recognition of human activity behaviour patterns, metaphors and higher level understanding which is useful to create an efficient system which can interact with humans as humans do.

The motivation behind the presented work is rapid ageing population in the world. According to (PACITA 2014), the proportion of the world's population over 60 years will double from about 11% to 22% between 2000 and 2050. The rapid ageing of population rises the following key points of interest;

1. Share of older people rise,
2. Economic consequences,

3. Expanded life expectancy,
4. Increasing demand for care services.

Technology and service innovations are expected to help responding to the demand for sustainable healthcare systems. The introduction of Information and Communication Technology (ICT) and Telemedicine is estimated to improve efficiency of health care by 20%, improving at the same time the quality of life of patients [EU, 2013 (page 6)].

Research to support senior citizens with technologies like tele-care, telemedicine, welfare technology, robotics, healthcare and AAL will play a key role. These technologies have the potential to enable seniors to live longer independently and securely at home, reduce hospitalization, socialize more easily/participate in society and live better in care and nursing settings.

1.2 Literature Review

In the context of independent living, the inference of user's current activity has been a very active research topic since 1990s. Moreover, activity recognition has become a multidisciplinary research area which connects its roots to multiple fields of study such as artificial intelligence, machine learning, human-computer interaction, ubiquitous computing and as well as neuroscience, physiotherapy, psychology etc. In my knowledge, the very first work of Caspersen et al., 1985, which describes the concept of activity, was published by *Public Health Reports*. The authors defined the common and professional uses of the terms “physical activity”, “exercise” and “physical fitness”. However, they are often confused with one another, and the terms are sometimes used interchangeably (Caspersen et al. 1985).

A physical activity (PA) is regarded as any bodily movement which results in energy expenditure (Caspersen et al. 1985). PAs have been studied in epidemiological research for investigating human movements and its relationship to health status, especially in the area of muscle weakness, mobility, cardiovascular diseases (Lyons et al. 2005), diabetes mellitus, gait balance and control (Lord et al. 2013)(Z. Rubenstein 2006)(Pappas et al. 2001), geriatrics training and stroke patients during rehabilitation (Chiang et al. 2013), fitness, obesity and health (Blair & Church 2004). A declining PA level represents a major factor in multiple illnesses and symptoms related to functional impairments (Blair & Church 2004). Thus, an automatic PA recognition system can help to understand physical health trends (Aziz et al. 2007) and design tailored interventions to improve physical activity.

The approach, I followed, towards making an effective and reliable PA recognition system started from detailed study of the published literature. At broad level, research is evolving in two separate communities, which are the medical community and the scientific community. The medical community published research describes their understanding about human activities and associated movements' importance in one's life. On the other side, the scientific community published research oriented towards measuring human activities and associated movements using technology. The assessment of medical work is not the scope of the presented work, thus I will focus on the well cited scientific work only. An overview of the literatures study with selected papers is described below to highlight some important observations.

In early 1990s, research started to observe walking patterns in elderly people or patients recovering from some specific symptoms mentioned above. In (Nicholson 1996), the author presented a case-study using a monitoring system and dynamic belief networks with computed threshold parameters. The author claimed that the system was effective in not only detecting falls but also irregular walking patterns, stumbles and near falls and early warnings of falls as well. In (Uiterwaal et al. 1998), the authors presented a validation study of ambulatory monitoring of physical activity in two working situations. The market product for ADL monitoring, *DynaPort*, was used to monitor basic activities; locomotion, standing, sitting, lying with one patient. Moreover, the patient's activity was videotaped during the experiment for validation purposes. In (Aminian et al. 1999), the researchers presented the feasibility study of *Physilog*, an ambulatory PA recorder based on accelerometer measurement, for monitoring activities. The activities were also recorded using video camera for activity labelling. In addition to the PA recording, the researchers developed an algorithm based on the thresholds analysis of the average and the deviation of the acceleration signal which classified the activities in four categories, i.e. lying, sitting, standing, and locomotion.

In (Wu 2000), the author proposed a methodology for extracting velocity-related features using video cameras. These velocity related features were used to distinguish fall related activities; tripping, forward and backward falls from standing, from normal activities; walking, rising from chair and sitting down, descending stairs, lying down etc. In (Noury et al. 2000), a self-developed device, named as *Actimeter*, was proposed for remotely monitoring human behaviour during daily life. The system was capable of recognizing two activities; standing and lying, and had the potential capability of detecting falls (if occurred during standing to lying). The activities were monitored through an infra-red sensor and a magnetic switch.

Until early 2000, the published research was showing trends in two directions: either towards monitoring physical activities or towards identifying scenarios of fall within physical activities, regardless if studies were evaluated in controlled/uncontrolled way with healthy/elderly subjects. In the meantime, sensing technology was also flourishing to produce electronic devices such as inertial sensors with remarkable advancements in micro-electromechanical (MEMS) technology. Especially accelerometer sensors became available on the market at low cost. These advancements made a positive impact in the healthcare field with new and innovative methods. As a consequence, the research trend drastically shifted towards identifying different physical activities using single/multiple accelerometer sensors and large numbers of papers were published after 2000. Some of the examples are the following.

The researchers (Mathie et al. 2001) described a novel system for monitoring physical activities: standing, sitting, lying, walking and transitions, in an home environment. An accelerometer sensor was worn at subject's waist. The system trial was conducted on patients with chronic diseases in an uncontrolled environment using pre-calculated threshold features extracted from accelerometer sensor data. In (Noury et al. 2003), the authors proposed a methodology to detect falls in real-time for elderly using a single body-worn accelerometer sensor. The sensor was attached to the subject's trunk. The proposed system was based on a threshold-based technique. Healthy subjects participated to the evaluation of the system in the controlled environment. The limitation of the proposed system is that each fall was simulated and authors considered a specific scenario of fall occurrence which is from standing to a laying position. In (Mathie & Celler 2004) the authors developed a generic framework for the automated classification of physical activities; standing, sitting, lying, walking and transitional activities; stand-sit, sit-stand, sit-lie and lie-sit with fall detection. A single accelerometer sensor was attached to the subject's waist using a belt. A total of 26 subjects participated in the data collection and framework evaluation experimental study done under laboratory conditions. The high performance of the developed framework based on threshold-based technique was reported with 97.0% sensitivity and 98.9% specificity. However in the discussion section, the authors reported that the system was able to accurately distinguish between activity (which include all reported activities) and rest in a free living environment. The system was unable to distinguish between standing and sitting which makes the reported results questionable. To measure performance of a binary classification test, sensitivity and specificity are the statistical measures used. Sensitivity (true positive rate) measures the amount of actual positives which are correctly identified. Specificity (true negative rates) measures the complementary to the false positive rate. In (Lyons et al. 2005) the authors proposed a threshold-based technique using simple features; mean and standard deviation, extracted from 2 accelerometer sensors attached to the subject's trunk and thigh. The activities; standing, sitting, lying and walking, were examined from one elderly subject in uncontrolled way in the hospital environment.

Machine learning algorithms played an important role in the last couple of decades. In data mining problems, machine learning provides classification techniques as well as clustering methods to find better solutions in many areas. In (Pirttikangas et al. 2006), a controlled study with 13 healthy subjects was reported. The dataset was collected using 4 accelerometers attached to wrists, thigh and neck. Activity classification was evaluated using two classifiers; multilayer perceptron (achieved accuracy 89.7%) and kNN (achieved accuracy 92.89%) for activities; stand, sit and relax, sit and watch TV, lie, walk, stairs climb/descend, read newspaper, drink, vacuum, typing, elevator up/down, run. An effective learning algorithm for constructing neural networks using acceleration measurements for activity recognition was presented in (Yang et al. 2008). The dataset for activities; standing, sitting, walking, vacuuming, brushing teeth and running, was collection using a single accelerometer worn at subject's wrist. The healthy 7 subjects participated for controlled experimental settings. The authors claimed of achieving 95 ± 3.76% using the proposed neural network against 87 ± 7.37% of kNN classifier. In (Gjoreski et al. 2011), an approach to fall detection with accelerometers that exploits posture recognition to identify postures that may be the result of fall was presented. The dataset for activities; standing, sitting, lying and transitional activities was collected using 4 accelerometer sensors placed at chest, waist, ankle and thigh. The random forest classifier was chosen for activity classification and achieved accuracy was in the range from 75% – 99%.

Between 2000 till 2012, many researchers presented their work in order to classify physical activities using either their own proposed threshold-based methodologies or already developed machine learning algorithms technique such as supervised; rule-based detection algorithms, kNN (Nearest Neighbourhood), Decision Trees (DT), Ensemble, Naïve Bayes (NB), Support Vector Machine (SVM), Artificial Neural Networks (ANN) etc., unsupervised; Hierarchical Modelling (HM), k-Means, DBSCAN, Expected Minimization, Gaussian Mixture Models (GMM) etc., and semi-supervised; Heuristic Models (HM). The wearable and non-wearable sensors were attached to different locations of the subject such as ear, neck, hip/waist, thigh, leg, foot etc. for activity classification comparison. Moreover, some researchers proposed techniques with the combination of activity monitoring and fall detection. In (Bagalà et al. 2012), the authors presented their findings with low specificity and sensitivity when accelerometer-related fall based detection algorithms (already published) were evaluated with real-world fall data. Another issue, I found, is to select right users/subjects for data evaluation with the proper understanding of the context where the system should be tested. In my literature review, most of the presented work was declared to be focused for the elderly in the context of independent living, assisted living, patients with gait problems, patients under rehabilitation etc. but, however evaluated under controlled laboratory conditions.

Furthermore, in (Mannini et al. 2013) the authors claimed to classify a wide range of activities; lying, sitting, internet search, reading, typing, writing, sorting files on paperwork, and standing still, indoor and outdoor cycling, natural walking, treadmill walking, carrying a box, and stairs up/down, sweeping with broom and painting with roller or brush. However, the authors present their findings with four compact activity classes; sedentary, cycling, ambulation and other activities which generate a question mark to the work against their claim of recognizing many activities.

The detailed analysis of the state of the art will be described in the next chapter. However in conclusion, there are many issues that motivate the development of new techniques to improve the accuracy under natural conditions. Some of these challenges are (1) the selection of appropriate users for whom system will be designed, (2) the construction of a portable, unobtrusive, and inexpensive data acquisition system with respect to desired subjects context, (3) with respect to context, selection of activities to be monitored, (4) the design of simple feature extraction and inference methods with less computational processing power, (5) the collection of data under realistic conditions, and (6) the flexibility to support new users with minimum system training.

1.3 Activity Recognition System (In my perspective)

In my understanding, at abstract level any activity recognition system is composed of four entities as shown in Figure 1; user, context, activity and sensor/s. All components are strongly interrelated to each other and influence the final result of the recognition system.

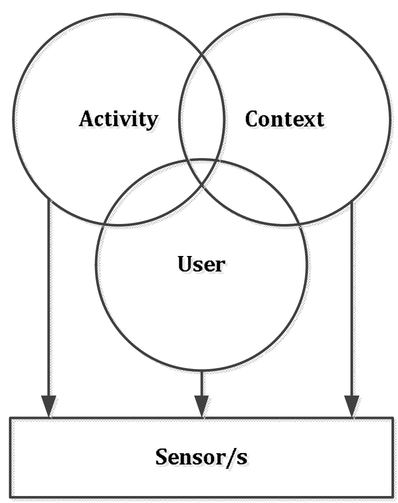


Figure 1 Activity Recognition Model Components

Physical activity in older people is usually performed as part of daily life activities, and thus activity monitoring should be continuously monitored with basic physical activities; such as standing, sitting, walking, and lying. Thus an effective recognition of these physical activities of older patients, over the long-term, is important in rehabilitation medicine not only to maintain physical and mental health but also for evaluating how activity is related to mobility and quality of life. Moreover, the short-term transitional activities between regular physical activities are also important in case of any unwanted events which are not limited to falls only. The presented work is focused on the elderly basic activities of daily life in the context described above.

In order to acquire user's contextual information, we require the availability of sensors which can provide necessary information. There are, however, kinds of information which can't be measured directly with one sensor. In this case, information has to be inferred from combination of sensors. At macro level, there are two approaches that have been employed for activity recognition: using wearable sensor/s; such as accelerometers, gyroscopes, magnetometers, pressure sensors, heart rate sensors etc. and using non-wearable sensor/s; such as infra-red sensors, magnetic switches, video cameras etc.. It is also important to consider the subject's acceptance towards these sensors and how many sensors subject is willing to wear.

A qualitative study (Boström et al. 2013) was conducted to identify and describe how older persons perceive monitoring technology in terms of personal privacy. The study identified uncertainty in terms of independence vs security and privacy vs intrusion. Older persons generally have positive feelings and attitudes toward technology and strive to maintain a sense of self confidence as long as possible, by having control. It is generally observed that with the passage of time the elderly prefer to continue to spend more time in their homes. Smart environments equipped with sensors and/or wearable body worn sensors to monitor activities may contribute to increased safety and independent living, according to one of the systematic review (Hawley-Hague et al. 2014).

In a home environment there are two prominent approaches that have already been employed for activity recognition: camera-based (non-wearable sensor) and accelerometer-based (wearable sensor) monitoring of activity. In a camera-based approach, a video camera/s is placed in room/home for subject's movements and classification of activities. This approach often work with good accuracy under laboratory conditions, however it is unable to provide the same accuracy under real conditions due to clutter, variable lightening and highly varied activities that take place in natural environment (Tapia et al. 2004). These devices are generally thought of as recording devices which also generate concerns of subject's privacy and invasiveness. Furthermore, the high installation and maintenance cost make this approach less feasible in real deployment of the system. On the other side, accelerometers are considered as less intrusive, low cost, small size and more reliable as compared to camera-based systems.

In the presented research work, the physical activity recognition system is developed for the recognition of basic daily life activities; standing, sitting, walking, lying and transitions, using a single accelerometer sensor for the elderly.

1.4 Problem Statement

The aim of this research is to design and develop an algorithm, for PA recognition system using single accelerometer sensor, which;

- Is extendible and can distinguish basic activities of daily life,
- Is robust, reliable and non-obtrusive,
- Requires less subject's data for classifier training,
- Gathers and process data in real-time.

The investigated research questions are the following:

Research questions:

RQ: How to design, develop and evaluate the classification algorithm for PA recognition using a single accelerometer sensor?

RQ 1.1: What is the optimal location of a single accelerometer sensor to detect the selected range of activities from sensor's data?

RQ 1.2: Which issues, related to activities selection and user's context using single sensor, are prominent in designing the PA recognition algorithm?

RQ 1.3: Which are the issues related to training dataset collection schemes and its impact on already developed machine learning algorithms in terms of accuracy and reliability?

RQ 1.4: Which are the issues related to feature/model parameter extraction from dataset associated with every subject?

RQ 1.5: How the accuracy and reliability of the PA classification algorithm can be improved with subject-dependent recognition system which require less training time to train the system.

1.5 Structure of the dissertation

The thesis is organized into the six chapters, described below:

Chapter 1: Introduction

The first section of the chapter describes the motivation behind activity recognition system and its importance in the context of elderly independent living. Then literature overview is presented which highlights the limitations of conducted research in terms of activities, context, subjects and sensors. The abstract model of the presented activity recognition system is described. Later, the primary research question and sub-questions in relation to state of the art are outlined.

Chapter 2: State of the art

The second chapter briefly described the related work in the area of physical activity recognition using wearable sensors. Initially it describes different types of wearable sensor used in activity recognition systems and reasons behind the selection of accelerometer sensor. Secondly, the chapter discusses how accelerometer sensors are considered to be effective in activity classification. How data was gathered; either controlled or in uncontrolled way, for different activities and which kind of feature parameters were selected, in reference to literature. Thirdly, the implemented methodologies and classification techniques already employed are discussed.

Chapter 3: Detailed description of research issues and methodologies

This chapter provides detail description of different challenges in the state of the art, in terms of complexity of activities, sensor requirements and its placement, acquiring training dataset issues, feature/model parameter analysis and real-time constraints in activity recognition research.

Chapter 4: Proposed activity recognition system

The chapter provides an overview of the proposed activity recognition system. It first describes the sensing devices used in this research for selected physical activities. Features extracted from sensor data are explained. Later, the importance of subject-dependent activity system is explained as a result of data analysis. The detailed description of the presented methodology and the reasons behind integrating statistical model and clustering method are explained for activity classification.

Chapter 5: Evaluation

This chapter describes in detail the evaluation procedure for the presented recognition system. The evaluation was conducted with a dataset collected in a controlled and an uncontrolled way.

Chapter 6: Conclusions

This section provides a discussion on the main results of the presented method and their relation to the existing work presented in the state of the art chapter. Furthermore, this chapter explains the contribution of this work and limitations are explained.

2 STATE OF THE ART

2.1 Introduction

Nowadays, every human is being surrounded and interacts in his/her daily life with many computers, electronic devices and sensors, which range from small to even nano-scale. The distributed behaviour of these computing devices, called *Ubiquitous Computing*, for humans becomes more interesting if designed to integrate user's context, i.e. information which is relevant to the current situation. Ubiquitous computing is to create such personal applications which can adapt and react to the current context of the user. This implies that context-awareness is one of main foundations of the ubiquitous computing. However, the term context itself is very broad, as explained by (Dey 2001),

> *Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application itself.*

One type of information is inferring *user*'s current *physical activity* in a specific *context*, i.e. environment. The inference of the user's current activity has been very important research topic which includes, but is not limited to, industrial applications, experiments and games, especially healthcare and assisted living etc. Consequently to acquire user's contextual information about physical activity, *sensor*/s devices are needed to build such a context-aware application. There are, however, kinds of information which can't be measured directly with one sensor. In this case, information has to be inferred from combinations of sensors.

Activity recognition has become a multidisciplinary research area which has its roots in multiple fields of study such as artificial intelligence, machine learning, human-computer interaction, ubiquitous computing and as well as neuroscience, physiotherapy, psychology etc. At broad level, research is evolving in two areas side by side, which are the medical community and the scientific community. The medical community published research describes their understanding about human activities and associated movements' importance in one's life. On the other side, the scientific community have developed systems that can identify human activities and associated movements using technology. The assessment of medical work is not the scope of the presented work, thus only well cited scientific work is considered.

Thus, the following chapter provides an overview of the literature work in physical activity recognition with the perspective of above mentioned four components.

2.2 Sensors

A wide range of sensors have been used for activity recognition. There are two prominent types of sensors that have been employed for physical activity recognition system: wearable sensor/s; such as accelerometers, gyroscopes, magnetometers, pressure sensors, heart rate sensors etc. and non-wearable sensor/s; such as infra-red sensors, magnetic switches, video cameras etc..

Non-wearable Sensors

This type of sensors range from relatively simple mechanism with discrete output, such as infrared sensors and magnetic switches (e.g. (Noury et al. 2000)), ball switches (e.g. (Laerhoven & Lo 2004)), RFID tag readers, to more complex sensing methods using computer vision (e.g. (Wu 2000), (Nam et al. 2013)).

In computer vision (camera-based) approach, a video camera/s is placed in room/home for subject's movements and classification of activities. This approach often works with good accuracy under laboratory conditions, however it is unable to provide the same accuracy under real conditions due to clutter, variable lighting and highly varied activities that take place in natural environment (Tapia et al. 2004). These devices are generally considered as recording devices which also generate concerns of subject's privacy and invasiveness. Furthermore, the high installation and maintenance cost makes this approach less feasible in the real deployment.

Wearable Sensors

Some researchers used ambulatory wearable sensing devices consisting of inertial sensors, (e.g. *DynaPort* (Uiterwaal et al. 1998), *Physilog* (Aminian et al. 1999)) for activity recognition. The sensors include different instruments, like accelerometers (e.g. (Mathie et al. 2001), (Ravi et al. 2005), (Olgu & Pentland 2006), (Gjoreski et al. 2011)), combination of accelerometers and gyroscopes (e.g. (Li et al. 2009)), combination of accelerometer and physiological sensor (e.g. (Parkka & Ermes 2006)), and force resistive sensors on foot with gyroscopes (e.g. (Pappas et al. 2001)).

Rapid enhancements in micro-electromechanical systems (MEMS) technology, makes it possible to manufacture small size accelerometer sensors which makes it possible to integrate them in smartphones. Some researchers developed smartphone applications for activity recognition e.g. (Khan et al. 2013), (Bayat et al. 2014).

In activity recognition using wearable sensors, accelerometer sensors are considered as most effective and capable of providing reliable measurements. Beside this, these sensors are low cost, require less energy, memory consumption, processing power and are fairly unaffected by environmental conditions. Moreover, wearable accelerometer sensors are considered as less intrusive as compared to camera-based systems.

Although a range of sensors have been used in the area of activity recognition, though accelerometer sensors have emerged as the most effective sensor for mobility assessment in both clinical and home environments.

2.3 Wearable Accelerometer Sensors

Accelerometer sensors are capable of measuring the applied acceleration along their axes. There are different types of accelerometers available, such as piezoelectric crystals, piezo-resistive sensors, servo force balance transducers, electronic piezoelectric sensors and variable capacitance accelerometers. Most physical activity recognition systems have used accelerometers which are capable of responding to acceleration due to gravity as well as acceleration due to movement.

2.3.1 Sensor placement

Figure 2 shows the three planes; transverse (horizontal), sagittal (vertical) and frontal (side), which intersect at center mass of human body (Winter 2004). The body center mass is often considered as important when studying activities and movements as it is important for control of whole body movements. However, the body center mass change dynamically and it is challenging to determine due to the complex dynamics of the human body.

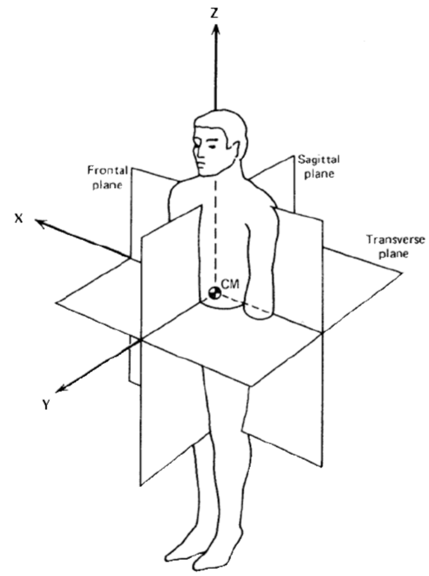


Figure 2 Description of Human Body

Usually, accelerometer sensors are attached to the part of body whose movements are under study. The accelerations generated during any movement may or may not vary among different humans, depending upon how particular activity/movement is performed. In order to study multiple activities researchers have used single accelerometer sensors at particular place of human body, as shown in Table 1. However other researchers have used multiple accelerometer sensors placed across different places of human body, as shown in Table 2.

Table 1 Activity recognition studies using single accelerometer at single location.

#	*Location*	*Reference/s*
1	Waist/Hip	(Mathie et al. 2001), (Mathie & Celler 2004), (Ravi et al. 2005), (Cleland et al. 2013), (Ellis et al. 2014), (Gao et al. 2014), (Gupta & Dallas 2014)
2	Foot	(Pappas et al. 2001), (Cleland et al. 2013)
3	Trunk	(Noury et al. 2003)
4	Chest	(Karantonis et al. 2006), (Cleland et al. 2013), (Nam et al. 2013)
5	Wrist	(Yang et al. 2008), (Cleland et al. 2013)
6	Lower	(Bonomi & Goris 2009), (Cleland et al. 2013)

#	Location	Reference/s
	back	
7	Thigh	(Cleland et al. 2013)
8	Pocket	(Khan et al. 2013), (Leppanen & Eronen 2013), (Fahim et al. 2013), (Kwon et al. 2014)

Table 2 Activity recognition studies using multiple accelerometer sensors at multiple locations.

#	Locations	Reference/s
1	Upper arm, Lower arm, Hip, Thigh, Foot	(Bao & Intille 2004)
2	Trunk and Thigh	(Lyons et al. 2005)
3	Head, Behind ear	(Lindemann et al. 2005)
4	Both wrists, Thigh, Necklace	(Pirttikangas et al. 2006)
5	Chest, Wrist	(Parkka & Ermes 2006)
6	Chest, Hip, Wrist	(Olgu & Pentland 2006)
7	Waist, Thigh	(Yeoh et al. 2008)
8	Chest, Thigh	(Li et al. 2009), (Chiang et al. 2013)
9	Chest, Waist, Ankle, Thigh	(Gjoreski et al. 2011)
10	Wrist, Hip	(Zheng et al. 2013)
11	Wrist, Ankle	(Mannini et al. 2013)

The design of an activity recognition system is usually determined by its purpose; context, activities to be monitored and duration of the activity monitoring. For example, in clinical environments when the objective is to acquire information in a short time and supervised way, large number of accelerometer sensors can be used. The information gathered in supervised monitoring situations leads to accurate assessment of the activities. However, the long-term activity monitoring which is usually occurred in unsupervised situations such as smart home, assisted living, or independent living of the subjects, subject's compliance becomes an essential requirement, if the system is to be used. A qualitative study (Boström et al. 2013) was conducted to identify and describe how older persons perceive monitoring technology in terms of personal privacy. The study identified uncertainty in terms of independence vs security and privacy vs intrusion. As one of the focus of this thesis is to monitor activities in unsupervised situations using single accelerometer sensor at one location which from one side could limit the number of activities to be monitored but could simplify the system design, its complexity, and usability and will be less intrusive. Moreover, increasing number of sensors not only increase the complexity but also the cost of the system.

2.4 Physical Activities

With wide range of available wearable sensors, it is not surprising that researchers have tried to recognize a wide range of activities. The authors, (Caspersen et al. 1985), defined the common and professional uses of the terms "physical activity", "exercise" and "physical fitness". The paper defined these terms with the hope that each definition will provide a framework in which studies can be interpreted and compared. The definitions of these terms were:

Physical Activity: It is defined as any bodily movement produced by skeletal muscles that result in energy expenditure. Physical activity in daily life can be categorized into occupational, sports, conditioning, household, or other activities.

Exercise: It is a subset of physical activity that is planned, structures, and repetitive and has as final or immediate objective the improvement or maintenance of physical fitness.

Physical Fitness: It is a set of attributes that are either health- or skill-related. The degree to which people have these attributes can be measured with specific tests.

The categorization of investigated activities in literature, itself, is a challenging task. Some researchers tried to recognize basic daily life physical activities such as standing, sitting, lying and walking using single or multiple accelerometers. The accelerometer sensors data has successful results in recognizing these activities, under certain conditions.

Another subclass of physical activities are called *Activities of Daily Living* (ADLs), as originally proposed by (Katz et al. 1963). ADLs are, for example, bathing, dressing, toileting, brushing teeth, and cooking, vacuuming, stairs climb/descend, laundry, watching TV, reading newspaper, typing, taking a cab etc. The ADLs are basic activities and used by physicians to assess function in daily life as well as their need for assistance in living.

Furthermore, the activities which can be considered as part of exercise such as running, cycling, jumping, rowing, squatting, dancing, basketball, hoping are studied using single/multiple accelerometer sensors. Table 3 presents the details of the activities investigated.

2.4.1 Fall Detection

Another kind of activity lies in the category of unwanted/unexpected events such as, but not limited to, falling. Due to rapid ageing, falls have been one of the biggest risks to especially elderly in terms of health and their well-being which leads to functional dependence. There are many fall detection systems solutions available on the market such as Philips AutoAlert, VigiFall, FATE-Fall detector for elderly, elderly medical alert system, Medical guardian FallAlert, Glaxy Fall detection system. Research has been and is still progressing in detecting fall using wearable sensors, includes accelerometers, gyroscopes, barometric pressure sensors and medical sensors such as ECG, EEG etc. Falls are a serious risk for the elderly, particularly for those living independently.

(Noury et al. 2000) proposed a fall detection system using an accelerometer, *actimeter*, with the approach of detecting falls where the initial position is stand and final position end up in lying. In (Noury et al. 2003) the authors proposed a methodology using 2 accelerometers that measures inclination and speed parameters from the sensor data. In (Mathie & Celler 2004), the authors emphasize the identification of transitional activities among standing, sitting, walking, and lying. The researchers claimed that fall related events could occur during transitional activities. Similar work has been done by (Karantonis et al. 2006). Some researchers (e.g. (Boyle & Karunanithi 2008)) developed their algorithms by simulating different fall related events in a controlled environment. In (Bianchi et al. 2010), a fall detection algorithm was presented using the combination of accelerometer and barometric pressure sensors. This study incorporates several protocols including simulated falls on the mattress and simulated activities of daily life. In (Bagalà et al. 2012), the authors presented their findings with low specificity and sensitivity when accelerometer-related fall based detection algorithms (already published) were evaluated with real-world fall data.

Although, accelerometer sensors have been proposed as being suitable for falls detection in the independent living context, there have been issues and challenges in the development of reliable falls detection systems. One reason is availability of real datasets containing fall events and need further work.

Table 3 State of the Art Review

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	Context	User (#)	Sensor/s	Classification Method
1	(Noury et al. 2000)	• Standing, Lying • Fall	Physical activity	NA	NA	Piezoelectric infrared sensor and a Magnetic contact switch	Threshold
2	(Mathie et al. 2001)	Standing, Sitting, Lying, Walking and Transitions (postures)	Physical activity	Uncontrolled Trial	Patients (NA)	Single accelerometer	Threshold
3	(Pappas et al. 2001)	• Walking (Gait balance) - Walk on flat and irregular surfaces • Stairs, step over small obstacles	Physical activity	Controlled	Healthy (10), Impaired gait problems (6)	3 force sensitive resistors on foot and single gyroscope	Rule-based detection algorithm
4	(Noury et al. 2003)	Standing-Bending-Lying (To predict Fall)	Physical activity	Controlled	Healthy (10)	2 accelerometers and single buzzer, push button	Threshold

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	Context	User (#)	Sensor/s	Classification Method
5	(Bao & Intille 2004)	• Walking, Sitting • Vacuuming, Laundry • Running, Cycling	• Physical activity • Exercise	NA	NA (20)	5 accelerometers	DT, kNN
6	(Mathie & Celler 2004)	• Walking, Transitions among sit, stand and lie, to predict • Fall	Physical activity	NA	NA (26)	Single accelerometer	DT
7	(Ravi et al. 2005)	• Sitting, Lying, Walking • Climbing stairs • Running	• Physical activity • Exercise	Controlled	NA (2)	Single accelerometer	NB, SVM, DT, kNN
8	(Lyons et al. 2005)	Sitting, Standing, Lying, Moving	Physical activity	Uncontrolled	Elderly (1)	2 accelerometers	Threshold
9	(Lindemann et al. 2005)	• Sitting, Lying, Walking • Climbing stairs • Running	• Physical activity • Exercise	Uncontrolled	Elderly (1)	2 accelerometers	Threshold
10	(Karantonis et al. 2006)	• Walking • Running, Jumping	• Physical activity	Controlled	Healthy (5)	Single accelerometer	DT

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	Context	User (#)	Sensor/s	Classification Method
		• Fall	• Exercise				
11	(Pirttikangas et al. 2006)	• Stand, Sit and relax, Sit and watch TV, Lie, Walk • Stairs climb/descend, Read newspaper, Drink, Vacuum, Typing, Elevator up/down • Run	• Physical activity • Exercise	Controlled	Healthy (13)	4 accelerometers	ANN, kNN
12	(Parkka & Ermes 2006)	• Lying, Sitting/Standing (as one activity), Walking • Running, Rowing, Cycling	• Physical activity • Exercise	Controlled	Healthy (16)	Single accelerometer and Physiological sensor	Custom-DT, DT, ANN
13	(Olgu & Pentland 2006)	• Stand, Sit down, Walk, Lay down • Crawl, Hand movements while standing	• Physical activity • Exercise	Controlled	Healthy (3)	3 accelerometers	HMM

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	Context	User (#)	Sensor/s	Classification Method
		• Run, Squat					
14	(Yeoh et al. 2008)	Standing, Sitting, Walking speed, Lying	Physical activity	Controlled	Healthy (5)	3 accelerometers	HM
15	(Yang et al. 2008)	• Standing, Sitting, Walking • Vacuuming, Scrubbing, Brushing teeth • Running	• Physical activity • Exercise	Controlled	Healthy (7)	Single accelerometer	ANN, kNN
16	(Bonomi & Goris 2009)	• Standing, Sitting, Lying, Walking • Working on a computer • Running, Cycling	• Physical activity • Exercise	Controlled	Healthy (20)	Single accelerometer	DT
17	(Li et al. 2009)	• Standing, Bending, Sitting, Lying, to predict • Fall	Physical activity	Controlled	Healthy (NA)	Single accelerometer	Threshold

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	Context	User (#)	Sensor/s	Classification Method
18	(Gjoreski et al. 2011)	Standing, Sitting, Lying, and transitions	Physical activity	Controlled	Healthy (11)	4 accelerometers	RF
19	(Zheng et al. 2013)	• Standing, Sitting, Walking, Lying down • Household chores • Running, Basketball, Dance	• Physical activity • Exercise	Controlled	age 5-15, Healthy (71)	2 accelerometers	Self-defined Model – Sub-window Ensemble Model
20	(Khan et al. 2013)	• Standing, walking, walking-upstairs, walking-downstairs • Running, Hopping	• Physical activity • Exercise	Uncontrolled	Healthy (30) for model evaluation, Healthy (10) for validation	Built-in accelerometer of smartphone	ANN
21	(Chiang et al. 2013)	• Standing, Sitting, Lying, Walking • Running	• Physical activity • Exercise	Controlled	Healthy (3)	3 accelerometers	Fuzzy algorithm

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	Context	User (#)	Sensor/s	Classification Method
22	(Mannini et al. 2013)	Authors classified activities in following classes, • Sedentary (Lying, Sitting, Internet search, Reading, Typing, Writing, Sorting files on paperwork, and Standing still) • Cycling (indoor and outdoor) • Ambulation (Natural walking, Treadmill walking, Carrying a box, and Stairs up/down) • Other activities (Sweeping with room and Painting with roller or brush).	• Physical activity • Exercise	Controlled	Healthy (33)	2 accelerometers	SVM

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	Context	User (#)	Sensor/s	Classification Method
23	(Cleland et al. 2013)	• Standing, Sitting, Lying, Walking • Walking up and down stairs • Running	• Physical activity • Exercise	Controlled	Healthy (8)	6 accelerometers	NA
24	(Leppanen & Eronen 2013)	Authors classified activities in following classes, • Idle/Still (Breakfast, Lying, Sitting, sleep, Standing, Still) • Walking • Running • Skiing • Cycling (Bicycling) • Vehicle (Car, Subway train, Taxi, Train) • Other (Cleaning, Cooking, Skating)	• Physical activity • Exercise	Uncontrolled	NA	Built-in accelerometer of smartphone	GMM, q-GMM
25	(Fahim et al.	• Walking, going up stairs, going down	• Physical activity	NA	Healthy	accelerometer	Genetic

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	Context	User (#)	Sensor/s	Classification Method
	2013)	stairs • Jogging, Running, Cycling, Hopping	• Exercise		(10)		algorithm
26	(Nam et al. 2013)	• Sitting-down, Standing-up, Walking forward, Walking backward • Turning left, Turning right, Going down stairs, Going up stairs, Taking an elevator	Physical activity	Uncontrolled	NA	Single accelerometer and single grid based image sensor	SVM
27	(Bayat et al. 2014)	• Slow-Walk, Fast-Walk • Stairs-up, Stairs-down • Running, , Dancing	• Physical activity • Exercise	Controlled	Healthy (4)	Single accelerometer	NA
28	(Ellis et al. 2014)	• Standing, Sitting, Walking • Riding in a vehicle • Bicycling	• Physical activity • Exercise	Uncontrolled	Healthy (2)	Single accelerometer	Random Forest

#	Reference	Studied activities	How activities were evaluated?				
			Activity Type	**Context**	**User (#)**	**Sensor/s**	**Classification Method**
29	(Kwon et al. 2014)	• Standing, Sitting, Lying, Walking • Running	• Physical activity • Exercise	Uncontrolled	NA	Single accelerometer	k-Mean, GMM, Hierarchical
30	(Gao et al. 2014)	Standing, Sitting, Lying, Walking and transitions	Physical activity	Controlled	Elderly (8)	Single accelerometer	ANN, DT, kNN, SVM
31	(Gupta & Dallas 2014)	• Sit/Stand (as one activity), Walking • Jumping, Running	• Physical activity • Exercise	Controlled	Healthy (7)	Single accelerometer	NB, kNN

Note: 'NA' corresponds to unavailability/unclear information from the reference paper. User represented as 'Patient' corresponds to real patient for study. User represented as 'Healthy' corresponds to either children or young adults for study. User represented as 'Elderly' corresponds to senior citizens for study.

In conclusion, physical activity recognition systems can be developed using a variety of wearable sensors with the capability of identifying a wide range of activities; basic daily activities, ADLs, and activities related to exercise. These wearable sensors can placed in many locations to get information about multiple activities or single location for more focused set of activities. The literature review identifies that the research community in the area of activity recognition is focused on two components; activity and sensor. In my understanding, the literature is lacking in highlighting the two other components of the system design for activity recognition which are the end user and the context. The recognition algorithm/model is the core of any activity recognition system with the integration of sensors. In order to evaluate the developed algorithm, sensors data acquired from under study activities are needed.

The next section will provide an overview of literature in terms of user and context for data collection.

2.5 Data Collection and Selection of Users and Context

Data collection is considered to be an important step in the development process of any computing system. In activity recognition systems, it is the process of gathering and acquiring information from sensor/s, in a systematic way that enables to answer research questions and to evaluate recognition algorithms. The objective is to collect reasonable amount of data and then through data analysis allow us to build concreate answers to the research questions. There are two methods of data collection.

2.5.1 Controlled/Supervised

Controlled experiments are a very common way of collecting data in almost every field. In activity recognition, in controlled experiments the researcher sets an experimental setup or pre-defined protocol for collecting data of each activity that needs to be studied. In order to conduct the experiment, two groups are needed: an experimental group (training group) and a control group (testing group). The training group is a group of users/subjects that are bound to perform any activity as described or set by the researcher in the experimental protocol. Each activity is labelled with the respective activity name/tag, which can be done either manually or through custom software. The dataset collected from the training group is used to evaluate the activity recognition algorithm or developed method. The testing group, on the other hand, is allowed to perform the activities without following the protocol. In principle, the data collected from testing group shouldn’t have any activity labels. Due to algorithm validation process, the data labelling is performed to training dataset as well.

On the positive side, the controlled experiments have the strength of establishing baseline information for the investigated activities. Experimentation done in controlled way can be repeated many times for algorithm model evaluation. It is difficult to answer, due to limited work done, if either results or conclusions made from controlled experimentation can be generalized for large sets of user population or not. On the negative side, controlled experiments can be artificial as they are conducted, for the most part, in a laboratory setting and therefore not able to include many real-life effects.

2.5.2 Uncontrolled/Unsupervised

The uncontrolled or unsupervised is another type of data collection method. In uncontrolled experiments, the users perform the unlimited number of activities in certain environment; such as clinical or home. The sensor/s is attached to one or multiple locations of body. The sensor/s data usually stored in the memory chip integrated with the sensing device. After collecting reasonable amount of data (for all activities), extensive data analysis is performed and the activity recognition algorithm is evaluated for certain activities. Due to the unlabelled dataset, machine learning techniques are used for activity classification and identification.

The literature study, as shown in Table 3, suggests that most data collections have been conducted in controlled environments with healthy subjects. There is very little work where datasets have been collected in uncontrolled situations with elderly or patients. Most of the research work done in activity recognition is being targeted to elderly users in different contexts of healthcare and assisted living situations which are considered to be uncontrolled environments. However, the experimentation, even in controlled way, with healthy subjects has not been validated in uncontrolled situations.

2.6 Activity Recognition Methodologies

Wearable accelerometer sensors have been used to devise algorithm methods for activity recognition system to classify different postures and movements. Some researchers develop systems using multiple sensors, and some use a single accelerometer sensor. Different body locations have been used to place wearable accelerometer/s which includes waist, chest, leg, thigh, foot etc. The datasets have been collected using the selected number of accelerometers located at single or multiple locations. The collected dataset is mainly the raw sensor data. The sensor data is, first, divided into small segments, referred as window-segments/windows. Then for each window, one or more feature parameters are computed. These feature parameters eventually become the input for developed activity recognition algorithm or already build classification methods which will associate each window with an activity.

2.6.1 Features selection

A wide range of features extracted from accelerometer sensors have already been studied. Table 4 highlights the most common features used in previous studies.

Table 4 Features Categorization

Category	*Feature*	**Reference**
Time-domain	Energy expenditure	(Mathie et al. 2001), (Bao & Intille 2004), (Ravi et al. 2005), (Cleland et al. 2013), (Ellis et al. 2014), (Gupta & Dallas 2014)
	Mean	(Bao & Intille 2004), (Mathie & Celler 2004), (Ravi et al. 2005), (Pirttikangas et al. 2006), (Lombriser et al. 2007), (Yang et al. 2008), (Yang et al. 2008), (Bonomi & Goris 2009), (Fernandez-Luque et al. 2010), (Gjoreski et al. 2011), (Atallah et al. 2011), (Zheng et al. 2013), (Gupta & Dallas 2014)
	Standard deviation and variance	(Kern et al. 2003), (Ravi et al. 2005), (Lyons et al. 2005), (Parkka & Ermes 2006), (Bonomi & Goris 2009), (Gjoreski et al. 2011), (Zheng et al. 2013), (Chiang et al. 2013), (Cleland et al. 2013), (Bayat et al. 2014), (Ellis et al. 2014), (Gao et al. 2014), (Gupta & Dallas 2014)
	Zero or mean crossing rate	(Maurer et al. 2006)
	Root mean square	(Maurer et al. 2006), (Luinge & Veltink 2005), (Bonomi & Goris 2009)
	Peak-to-peak values	(Van Laerhoven & Gellersen 2004), (Parkka & Ermes 2006), (Bonomi & Goris 2009), (Zheng et al. 2013)
	Maximum and minimum	(Bayat et al. 2014), (Ellis et al. 2014)
	Correlation between pair of axes	(Ghasemzadeh et al. 2008), (Ravi et al. 2005), (Yang et al. 2008), (Bonomi & Goris 2009), (Zheng et al. 2013), (Cleland et al. 2013), (Bayat et al. 2014)

Category	*Feature*	**Reference**
Frequency-domain	Spectral energy	(Bao & Intille 2004), (Bonomi & Goris 2009)
	Spectral entropy	(Preece et al. 2009), (Ellis et al. 2014)
	Spectral centroid	(Wu et al. 2008)
Time-frequency domain	Wavelet transform	(Preece et al. 2009), (Li et al. 2013)

Generally, features are the parameters extracted from the sensors which can easily discriminate one activity from another. Existing research indicates the variability of selected features, even for the same activity. Thus one can infer that subjects may or may not perform the same activity in different ways which leads to the fact of features variability. Hence, to achieve effective activity classification, selecting features with high discriminative ability is of high importance.

There are numbers of ways that have been used for selecting appropriate feature sets for activity recognition. The statistical analysis approach is to assess the distribution of selected time-domain feature/s for different activities, e.g. (Lyons et al. 2005). Another approach is forward-backward search in which features can be added or removed from a larger feature set. Importantly, the final optimal features are identified depending upon the classification accuracy achieved for each feature subset e.g. (Bayat et al. 2014). Some researchers used another approach where, instead of selecting a subset of features, features were combined to make a new set of features. This approach is often useful in reducing the number of features, where the dataset is being collected from many sensors, which are either unnecessary or need more computational work. This approach is called feature reduction. Principle Component Analysis (PCA) and Independent Component Analysis (ICA) are two commonly used feature reduction techniques used in activity recognition with multiple sensors, e.g. (Habilitationsschrift 2005).

As far as frequency domain and time-frequency domain parameters are concerned, these features are computed by first transforming the window-segment into frequency domain, these parameters need complex computation to discriminate physical activities, longer window-segments are required for these feature calculation. Due to increase in computational time and power, these feature techniques are inappropriate for real-time application.

On the other hand, time-domain parameters, typically of statistical manner, require less computational time and can be extracted easily in real time. These features are still the most widely used features in many acceleration-related activity recognition systems.

As a result of selecting a feature set which can classify the sensor data to particular activity, it will become the input to the classification algorithm. The complexity of these classification algorithms varies from simple threshold-based methods to more advanced algorithms such as Machine Learning (ML) techniques.

2.6.2 Fixed Threshold-based Methods

The published research work have used mostly time-domain features to develop activity recognition methods called as *Fixed Threshold-based Methods* that use feature set parameters assigned with fixed value or pre-determined value as a result of investigation. Literature, published results, for activity recognition using threshold-based methodology showed better results in controlled situations because such methods developed with the assumption that acceleration signals are deterministic. Threshold-based methods have been used successfully in discriminating static activities, such as standing, sitting and lying, and dynamic movements; walking, running, jumping etc., using single accelerometer sensor worn at waist/trunk ((Mathie et al. 2001), (Noury et al. 2003)) and multiple accelerometer sensors worn at trunk/thigh/head/ear/chest ((Lyons et al. 2005), (Lindemann et al. 2005), (Li et al. 2009)). However, acceleration signals generated in response to any activity are not deterministic due to the complex dynamics of the human body. Thus, there is the possibility for developing a better mathematical model by using discrete time-series data analysis to describe the acceleration signals.

2.6.3 Machine Learning Techniques

The following section provides a brief and general overview of the machine learning techniques that have been used in the literature for activity recognition – for a detailed description and mathematical model for each technique see e.g. (Witten et al. 2011). A wide range of classification methods have been employed, as shown in Table 3. The comparison of different methods becomes difficult due to few reasons. First, there is a lack of standard datasets available for each activity. Usually, every ML technique works under a certain mathematical model. However, it is not evident from the literature why different researchers used different techniques for the similar type of activities. Secondly, the researchers' selected ML technique usually depends on the selected activities and type of sensors data.

Machine learning techniques are generally categorized into supervised, unsupervised and semi-supervised. Each learning technique has its own pros and cons. More research evidence is required to know which learning technique should be applied at any particular situation.

Supervised Learning Technique

Supervised learning techniques require a training phase where labelled data of each activity is provided to an algorithm. Once, the algorithm is trained then there is a testing phase where the algorithm is able to classify, or to assign, correct activity for which it is trained. Some supervised learning techniques used in the literature are kNN (Nearest Neighbourhood), Decision Trees (DT), Ensemble, Naïve Bayes (NB), Support Vector Machine (SVM), Artificial Neural Networks (ANN) etc., as mentioned in Table 3.

The general procedure for supervised learning algorithms for activity recognition consists of the following steps:

Sensor data acquisition for each activity with labels, as described in Section 2.5.1, usually referred as true value or ground truth.

1. Feature extraction and selection
2. Dividing each activity dataset into train and test dataset
3. Train dataset is used for algorithm or classifier training

Test dataset is used for predicting algorithm performance, in terms of accuracy, precision, sensitivity, specificity etc. Cross-validation (CV) approach is used to evaluate the accuracy of the recognition system.

Unsupervised Learning Technique

The unsupervised learning techniques require neither training phase nor the labelled activity dataset. The unsupervised clustering method e.g. *k-Means* work with the objective to partition *n* data samples to *k* clusters in such a way that each data sample belongs to nearest mean value (pre-determined by k-Means algorithm based on data distribution). For example, if the dataset is composed of 4 activities then the clustering methods require selected *feature set* and *k value (number of clusters)* as an input parameter. The chosen clustering method distribute the dataset into *k* clusters. Unfortunately, clustering algorithms can't identify the cluster label, hence need careful offline work. Unsupervised learning techniques used in literature are Hierarchical Modelling (HM), k-Means, DBSCAN, Expected Minimization, Gaussian Mixture Models (GMM) etc., as mentioned in Table 3.

The general procedure for unsupervised learning algorithms used for activity recognition consists of the following steps:

i. Data collection from body attached sensors without labels
ii. Feature Extraction
iii. Application of already developed clustering models

The claimed classification results have shown variation among different clustering algorithms which makes difficult to evaluate the applied clustering algorithms. The conducted research indicates few approaches to validate the selected algorithm's performance; such as using camera, hiring an observer, offline data processing.

For example, a camera-based validation study was conducted by researchers (Wu 2000) for distinguishing fall-related activities from normal activities; standing, sitting, walking and lying. The dataset was collected using a single body-worn wearable accelerometer sensor attached to subject's trunk. The threshold-based approach was used to classify normal activities and the proposed system was validated using cameras installed in the room.

In another study, for example, researchers (Lyons et al. 2005) assigned an observer to the patient in the hospital environment. The activity recognition system was designed for patient's mobility monitoring, for standing, sitting, lying and walking activities. The dataset for the mentioned activities were collected in an uncontrolled way. However, as mentioned above, one observer was assigned to the patient and recorded the patient's activity without interacting with the patient. The research was done by using two accelerometers attached to the subject's trunk and thigh. After collecting reasonable amount of data, the activities classified by proposed threshold-based algorithm was compared with the observer's records. All data processing, algorithm evaluation and validation were done in offline mode. The findings indicated 93% accuracy.

In (Kwon et al. 2014), the authors conducted an uncontrolled data collection study using a smartphone placed in the subject's pocket. The study was based on assessing the effectiveness of different unsupervised learning algorithms and consists of two parts; when k (number of activities) is known and when k is unknown. The authors selected k-Means, Gaussian Mixture Models (GMM) and Hierarchical clustering methods for activity classification. The dataset for activities; standing, sitting, lying, walking and running was collected, for 10 minutes, from the subject. Their findings indicate 71.9% accuracy for k-Means, 100% for GMM and 79.9% for hierarchical clustering.

Semi-supervised Learning Technique

The third category of machine learning techniques is semi-supervised learning. The semi-supervised technique tries to merge the concepts of supervised and unsupervised learning techniques. Although, there is very little work in this domain however it is quite interesting in the area of activity recognition systems. The semi-supervised approach has been applied when less labelled data and comparatively large unlabelled data is available; when it is usually expensive to acquire continuously labelled data. In (Khan et al. 2013), the authors developed their own activity recognition algorithm integrated in a smartphone for: standing, walking, running and hopping. The evaluation of the developed model was done by 30 healthy subjects and for validation 10 healthy subjects participated. During the validation phase, each subject was carrying the smartphone while performing the activities. A mobile application at certain moments indicates the name of the activity the user is doing. However the subject has to identify the correct activity to the application for developed algorithm calibration. The developed system showed 87.1% accuracy in classification of the selected activities.

2.7 Conclusion

This chapter elaborates the literature work introducing two considerations, the first is the importance of wearable sensors in the activity recognition area and the second the large variety of activities that can be identified using wearable sensors. Within wearable sensors, the accelerometer sensor/s showed significant attention towards activity recognition. These accelerometer sensors can be attached to the subject's body at different locations such as waist, hip, thigh, chest, wrist for selected activity data collection.

The chapter also describes different data collection schemes used for acquiring activity dataset and which kind of features can be extracted from these datasets. After feature selection for selected activities, the next step is either to develop an activity recognition algorithm or utilize the already developed wide range of classification and clustering methods of machine learning. Time-domain features are commonly used in developing threshold-based methods, as these features require less computational time and power to build real-time recognition systems. As the threshold-based methods usually work with pre-determined feature values, the research indicates that the selected features may or may not have data variability which could depend on the data collection scheme or the activity selection. Researchers have applied many machine learning algorithms in order to achieve more accuracy by applying different ML techniques. Published works cover many ML algorithms and the interesting point is to compare accuracy claimed with ML algorithms. The reason of this wide variability could be the size of the dataset, data collection protocol, subjects group, environment, number of sensors, sensor placement etc. Some researchers have also presented their own algorithms.

Therefore considerable further work is required to establish the suitability of the different techniques for a range of classification problems. Most previously published activity monitoring studies vary considerably in the choice of sensor placements and in the range of activities analysed.

3 RESEARCH ISSUES AND CHALLENGES USING WEARABLE SENSORS

3.1 Overview

The literature in the area of physical activity recognition is wide spread ranging from different types of sensors that can be used to identify variety of activities in different contexts.

Physical activities have been studied in epidemiological research for investigating human movements and their relationships to health status, especially in the area of muscle weakness, mobility, cardiovascular diseases (Lyons et al. 2005), diabetes mellitus, gait balance and control (Lord et al. 2013)(Z. Rubenstein 2006)(Pappas et al. 2001), geriatrics training and stroke patients during rehabilitation (Chiang et al. 2013), fitness, obesity and health (Blair & Church 2004). A declining PA level represents a major factor in multiple illnesses and symptoms related to functional impairments (Blair & Church 2004). Thus, an automatic PA recognition system can help to understand physical health trends (Aziz et al. 2007).

The automatic recognition of PA using wearable sensors has practical limitations from subject's perception, such as number of sensors and location of sensors. There are other issues that influence in the successful deployment of activity recognition system.

3.2 Complexity of Activities, the Selected Subjects and Context Influence

The developed systems in the field of activity recognition using wearable sensors can be evaluated in terms of identified activities complexity with respect to selected subjects and the subject's context. The recognition systems complexity can vary depending on different factors, which can include; number of activities, which subjects, which context, kind of activities and issues related to acquire training dataset for the selected activities.

3.2.1 Number of activities

Human body dynamics is capable of generating different types of activities. There could be inter-subject and intra-subject variability in performing activities. The human activities can be identified either by using single/multiple wearable sensors or with combination of different type of wearable sensors. The selected activities and sensors should be able to recognize these activities. Multiple or combination of sensors could be useful and could have the capability to identify the large set of activities, with certain concerns, if the recognition system is designed for short-term use. However, in case of long-term recognition, it is usually easier to recognize a subset of activities than large number of activities. Hence, it is more useful and would be more meaningful to recognize small set of activities, with reasonable accuracy, which have more impact in one's independent living.

3.2.2 Which subjects and contexts?

The published work proposed recognition systems for elderly subjects in the context of their independent living, assisted living etc. in terms of their healthy and active life. However, the experimentation conducted was based on healthy subjects and in controlled laboratory environments. The published work is mostly based on either pilot or preliminary studies with no future implementation of their initial findings (to my knowledge). Few researchers conducted their studies with real patients or elderly in uncontrolled environments; however, more research work is required in this domain. As mentioned before, the subject could perform the same type of activity differently in a different context of living. It is very important to decide the ultimate user and associated context in the development of activity recognition system. Thus, the proposed system should be capable of identifying the same activity correctly, at least for the same subject. In the context of, e.g., independent living of elderly, the proposed system has to be less intrusive and easy to use with an objective of utilizing recognition system for longer period of time.

3.2.3 Which kind of activities?

The basic activities are considered to be the important in every ones daily life. In the context of elderly's well-being and activeness, these basic activities play an important role and can be recognized using single wearable sensor. However, other household activities are also important, but probably require more sensors to be attached on the body. The activity recognition system can achieve simplicity with single wearable sensor to recognize basic activities of elderly. The other activities can be identified by exploiting non-wearable sensors; such as ambient sensors, with the help of indoor-localization techniques as explained in e.g. (Merico et al. 2012; Merico et al. 2013).

3.2.4 Training dataset collection issues

For algorithm evaluation, a train dataset is required which can be collected either in a controlled laboratory environment or in an uncontrolled environment, as described in the Section 2.5.

Usually, dataset collected in laboratory settings use protocols, pre-defined by the investigator. Thus the subjects performed activities are, probably, with same speed and for less time. The probability of acquiring unnatural activity patterns for the subjects are high, due to the fact that subject has to follow the protocol in strict manner.

However, in free living or uncontrolled conditions, the dataset is collected in unsupervised way. Hence, the subject might perform the same activities differently than the controlled laboratory conditions. The understanding of human behaviour, while performing any activity, in an uncontrolled environment is still a challenging work.

On the positive side, it is easy to label the subject's activity during laboratory conditions and a mandatory task for activity recognition algorithm's evaluation. Therefore, the training dataset collected for activities in controlled settings are usually easier and ultimately the algorithm's evaluation produces good results. On the other side, the dataset collected in unsupervised/uncontrolled settings brings several challenges in terms of validating the algorithm when there is no labelled data. The approach to label data in uncontrolled way, described in literature, is accomplished either by the help of external observer, or the subjects themselves labelled the activity. These scenarios generate another problem, if the activity data labelling is incorrect or unreliable then it will affect the classifier's training and eventually decrease the recognition accuracy.

3.3 Sensor Requirements and Its Placement

Among wearable sensors, the accelerometer sensor/s has been successfully used in the activity recognition system in classifying different activities. The activity recognition systems developed using small set of sensors are capable of recognizing small set of activities, such as basic daily life, which are easier in terms of collecting training dataset and more appropriate to real-world applications. The real-world applications are built with the concept of working in real-time conditions. Towards building real-time applications, small number of sensors means fewer signals are needed to analyse and less computational complexity as compared to the systems with large set of sensors.

Furthermore, the published research indicates that the single accelerometer sensors have the potential to recognize/identify activities, if algorithms have been developed within the subject's context and selected activities. Some researchers have conducted studies for optimal location of single accelerometer sensors e.g. (Cleland et al. 2013)(Gao et al. 2014) and findings showed that the subject's waist could be the optimal location for specific activities and can achieve reasonable accuracy in recognizing different physical activities.

The literature review demonstrates that useful information can be obtained using single accelerometer sensor attached to subject's waist (e.g. (Mathie et al. 2001), (Mathie & Celler 2004), (Ravi et al. 2005), (Yang et al. 2008), (Cleland et al. 2013), (Ellis et al. 2014), (Gao et al. 2014), (Gupta & Dallas 2014)); considered as close to center of mass of the subject (Winter 2004).

Moreover, the sensor's placement on the subject's body has major impact in the classification of activities. Some activities can be classified with more accuracy at certain sensor's location, and some other at different location. More sensors attached to the subject's body might be acceptable for short-term activity monitoring in controlled situations, however, they are not that much feasible for long-term activity monitoring in uncontrolled situations.

Thus, in the context of independent living, the developed system should consider subject's tolerance towards wearing sensors and this can be achieved by using single body-worn accelerometer sensor to recognize activities with high accuracy.

3.4 Training Dataset and its Impact on The Recognition Algorithm's Performance

As described before, activity dataset can be collected in either controlled or uncontrolled environments. Moreover, generally, there are two approaches being used to develop activity recognition system which includes either *Threshold-based methods* or *Machine learning techniques* (Supervised/Unsupervised). To explain the impact of training dataset to algorithm's recognition accuracy, the subset of literature is selected where researchers developed/proposed/used algorithms for basic activities such as standing, sitting, lying and walking using single/multiple accelerometer sensor.

It appears to me that a reasonable amount of each activity dataset is required for threshold-based methods to compute feature thresholds which can discriminate one activity from another. These methods becomes challenging, e.g., how much data is required? Which features to be used? Will the pre-determined threshold values, for selected features, be reliable enough for large subject population? As mentioned before with reference to the literature that the activities performed by human body could be different at different situations, which results in variations in achieved system's accuracy, as shown in Table 5. Furthermore, different subjects might perform the same activity in different way. There is lack of research evidence for the validation of already proposed threshold-based methods with selected feature set.

On the other side, machine learning techniques deal with the development of activity recognition systems that are meant to learn from the data. Therefore, machine learning techniques require two types of datasets; one called a train dataset and the other as a test dataset. The train dataset, collected from given subjects, is used for classifier (of selected technique) training/learning. The test dataset, collected from unobserved subjects, is used for trained classifier evaluation. The objective of this training phase is to achieve generalization, leads to subject independent recognition. Generalization in this context is the ability of the classifier to perform accurately on new, unseen subjects after learning from the training dataset. Unfortunately, neither there are any training data collection protocol standards nor any agreements on the size of training/testing dataset are mentioned in the literature. As shown in Table 5, the variations in achieved recognition accuracy for even basic activities is due to different amount of data gathered for different number of subjects or due to the reason that there is inter or intra-subject data variability. Moreover, different researchers have claimed different recognition accuracies for different machine learning techniques. The challenges in the adopting machine learning techniques are, 1) the quantity of training dataset collection, 2) subject-independent or subject-dependent training, 3) data labelling issues in supervised learning techniques, 4) data labelling requirement for unsupervised learning techniques for validation purposes, 5) feature selection, 6) classifier selection and 7) addition and identification of new activities.

Table 5 A selected review of basic physical activity (stand, sit, walk, lying) using accelerometer sensor / s.

Ref.	*Context*	*Dataset (Subjects)*	*Sensor*	*Method*	*Accuracy*
(Mathie et al. 2001)	Uncontrolled	14 hrs (NA)	1	Threshold	NA
(Lyons et al. 2005)	Uncontrolled	29 hrs (1)	2	Threshold	93%
(Yeoh et al. 2008)	Controlled	NA (5)	3	Heuristic Model	100%
(Li et al. 2009)	Controlled	<5 min (NA)	2	Threshold	91% Sensitivity
(Gjoreski et al. 2011)	Controlled	15 min (11)	4	Random Forest	75%–99%
(Chiang et al. 2013)	Controlled	70 sec (3)	3	Fuzzy algorithm	99.33%
(Cleland et al. 2013)*	Controlled	7 min (8)	1	SVM, J48, NB, NN	97.81%, 94.11%, 95.92%, 97.75%
(Kwon et al. 2014)	Uncontrolled	NA	1	k-Means, GMM, Hierarchical clustering	71.98%, 100%, 79.98%
(Gao et al. 2014)*	Controlled	340.5 min (8)	1	Decision Tree	92.8%

Note: References in red colour indicates the participation of elderly/patient in data collection and black colour references collected data from healthy subjects. NA means information is not clearly available. *Reference conducted studies for evaluating different accelerometer sensors location and classifiers comparisons, accuracy w.r.t single sensor attached to waist are presented.

3.5 Conclusion and the Proposed Solution

Most of the published work in the area of activity recognition systems is mainly focused on a number of sensors attached at different locations and a number of physical activities. As explained before, the ideal activity recognition system is a combination of, not only, sensors and activities but also the end user and the context of system's use. There should be a trade-off among these components which ultimately provide a reliable recognition system performance.

As mentioned before, the approach of utilizing more sensors although they have the capability to recognize more activities is not feasible for long-term and uncontrolled activity monitoring system deployment due to issues like invasiveness, cost, difficult to use etc. Relatively, few studies have been conducted with single accelerometer sensor attached to subject's waist in uncontrolled situations. Such systems with single accelerometer sensors provided good accuracy results in the past, however, failed to achieve the same accuracy for basic activities of daily life such as standing, sitting, walking, lying and transitional activities. The transitional activities were considered to be important in the literature to detect unwanted events such as, but not limited to, falls. Thus for the presenting thesis work, the basic activities of life and transitional activities are considered.

A wide range of feature sets, both time and frequency-domain, have been investigated in the past, however showed variation in terms of recognition system's accuracy. As explained before, frequency domain features require high computational power and time to distinguish different activities. Time-domain features, on the other side, require less computation and can easily be extracted in real-time. The features mean and standard deviation were chosen in order to discriminate activities and for transitional activities identification. The published results, in terms of accuracy, indicate the presence of high variability in the selected features and classifiers which might be because of the way subjects performed activities. The results suggest that there may or may not be inter or intra-subject data variations in the features. The construction of a subject independent classifier is a challenging task and requires the train datasets from large subject's population. Moreover, some work, such as (Bao & Intille 2004), strongly suggest that subject independent recognition of activities is hard to attain. In case of subject-dependent recognition systems, the issue of training dataset and data labelling will be limited to a particular subject and can achieve reliable accuracy rate in both controlled and uncontrolled situations. Furthermore, the system can be recalibrated by acquiring a new training dataset, if possible, as explained in (Fahim et al. 2013).

The most of the past work in activity recognition is conducted in controlled laboratory environments with limited amount of activity datasets. As seen, the classification accuracy achieved in controlled experimentation is quite high. However, there is very few work conducted in uncontrolled environments. The researchers claimed to provide activity recognition solutions for elderly, in the context of independent living. The proposed systems were pilot/preliminary studies which lack from the validation point of view in real-world scenario. In case of unlabelled data the traditional clustering techniques were used for activity classification. In conventional clustering methods the algorithms' objective is to partition *n* data points into *k* clusters in such a way that each data point belongs to the cluster with nearest mean (centroid). The proposed methods, in the past, generally rely on a controlled supervised training. Therefore, by applying different clustering algorithms end up in identifying different classification accuracy for the same type of activities, as shown in Table 5.

In order to overcome fixed thresholds and clustering problems, we propose a semi-supervised subject-dependent clustering approach which requires limited amount of labelled data in order to compute centroids for activity clusters. Later, the subsequent assignment of new data to clusters' centroid is conditioned to a physical activity transition model. The next chapter will explain the proposed recognition methodology for the basic activities of life and transitional activities using single accelerometer sensor attached to subject's waist.

4 PROPOSED RECOGNITION SYSTEM

The following chapter presents an overview of the activity recognition system that is the result of the thesis. It also describes the research approach used to collect training data for the development of an algorithm model and its evaluation.

4.1 Overview

Every human being experiences and performs different activities throughout his/her life, which may or may not differ from one subject to another. In order to infer any activity, a wide range of sensors can be used. However, making a complete inference of any activity using a combination of sensors is possible but not practical. If complete and detailed description is required, then video data is necessary. In this work, this is not the case, so video data were not recorded during acquisition of data set used due to privacy concerns.

The objective of the presented work is to design and develop an algorithm for activity recognition with the following requirements:

- It should be able to correctly recognize basic normal activities; stand, sit, walk, lay and all transitions among these activities.
- It should be user friendly and non-obtrusive.
- As much as possible the system should be battery operated.
- The data gathering and processing must be done in real-time to achieve immediate response to subject's actions.

In order to devise such a system, I followed these steps.

1) Firstly, activity data sets were collected for physical activities from different subjects under laboratory conditions.

2) Once data sets were collected, a systematic analysis was performed to determine the relevant parameters for recognition algorithm with real-time performance.

3) The classification algorithm was developed to evaluate the parameters extracted from the second step.

4) The developed algorithm was validated by acquiring data set in real-time.

4.2 Sensor Devices

In this research, data collection for model development evaluation and validation was done by using two sensors.

4.2.1 A Custom-build Data Acquisition Device

A custom-build data acquisition network device, called Mobile Device (MD), as shown in Figure 3, that includes a Jennic JN5148 transceiver (Jennic 2014) and a InvenSense MPU-9150 motion tracking device (InvenSense 2014) was used. The JN5148 is an ultra-low power, high performance microcontroller with 2.4GHz IEEE802.15.4 compliant transceiver. The MPU-9150 is an integrated 9-axis motion tracking device that combines a 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer and a Digital Motion Processor hardware accelerometer engine that runs on low power at 2.4V to 3.46V. The MPU-9150, 3-axis accelerometer, provides digital output with programmable full scale range of ±2g, ±4g, ±8g, and ±16g at sampling frequency of 20 Hz.

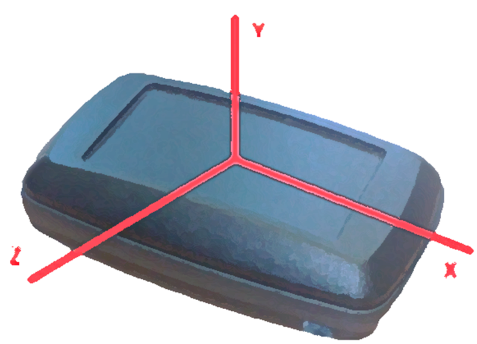


Figure 3 A Custom-built Mobile Device

4.2.2 Gt3x Ambulatory Monitoring Device

The GT3X+ ambulatory monitor (Llc 2014), shown in Figure 4, uses a 3-axis accelerometer and ActiGraph's proprietary digital filtering algorithms to measure the amount and frequency of human movement. The raw data collected by the GT3X+, at sampling frequency 30-100Hz, can be reviewed directly or further processed through ActiGraph's digitally matched filter. This digital filter bandlimits the accelerometer to the frequency range of 0.25 to 2.5Hz, which has been carefully chosen to detect accelerations caused by normal human motion.

Figure 4 GT3x Ambulatory Monitoring Sensor

4.3 Physical Activities

The activities to be investigated were classified into two categories:

- Static Postures:
    - Standing: This implies that the subject is standing in his/her natural way.
    - Sitting: The subject is sitting on a chair.
    - Lying: The subject is lying on the floor where the trunk and the hip are at the same level.

  Static postures may include some movements while remaining in the same posture.

- Dynamic Posture:
    - Walking: Walk is an activity which is evolved from stand posture with a significant movement.

  The above mentioned activities were considered as basic activities of life.

- Transition Activities:

  These are the activities where the subject goes through a transition phase while moving completely from one static activity/posture to another. Transitions are the postures which occur for short time.

    - Standing to Sitting

- Sitting to Standing
- Sitting to Lying
- Lying to Sitting

- Abnormal activities: These are the activities which are hard to define and non-trivial. There is no concrete definition of abnormal activities yet. However, this work considers all the activities which are not explicitly defined as abnormal activities.

4.4 Assumptions

The following assumptions were made while developing physical activity recognition algorithm.

4.4.1 Sensor and Its Placement

The body worn single tri-axial accelerometer sensor was attached to the subject's waist by a belt. If the sensor is hanging freely, then the sensor's reading will not represent the subject's movement and cannot be considered for subject's activity.

Subject has to be in standing position at the beginning of the experiment.

4.4.2 Physical Activity Transition Model

A Physical Activity (PA) performed by a human body (subject) is a combination of static postures and dynamic movements. In the context of basic activities of daily life, static postures can be defined as STAND, SIT, LAY and WALK. The subject remains in the same static posture unless there is a movement or a transition occurs. However, static postures may still include some movements while remaining in the same posture.

The subject goes through a transition phase while moving completely from one static posture to another. For example, STAND-SIT is the transition state while moving from the STAND posture to the SIT posture.

Moreover, there is the possibility of returning back from a transition state to the previous static posture which can be identified as one form of dynamic movement. For example, subject enters in the transition state STAND-SIT and returns back to the STAND posture.

In this approach, WALK and RUN are activities that evolve from the STAND posture with a significant factor of movement which is subject-dependent.

Another possibility is that the subject performs the same posture in a different context; for example, the subject is sitting either on the ground, or on the couch, or while driving a car etc. In order to distinguish this SIT (posture) in different contexts requires either interaction with the caregiver or the system needs to be trained to recognize this particular posture. In this scenario, the current methodology will recognize an abnormal activity that later will become part of the basic activities, if the caregiver considered it as a normal activity. However, in (Noury et al. 2008), the researchers described the phenomenon of critical events, such as a fall, which could probably be more likely to occur during transitioning phases of normal activity. It is difficult to describe precisely the phenomenon of fall, and even harder to imagine the means for its detection.

In our opinion, PAs performed by any subject can be modelled with natural behavioural rules as described above and can be considered as hypothesis as shown in Figure 5.

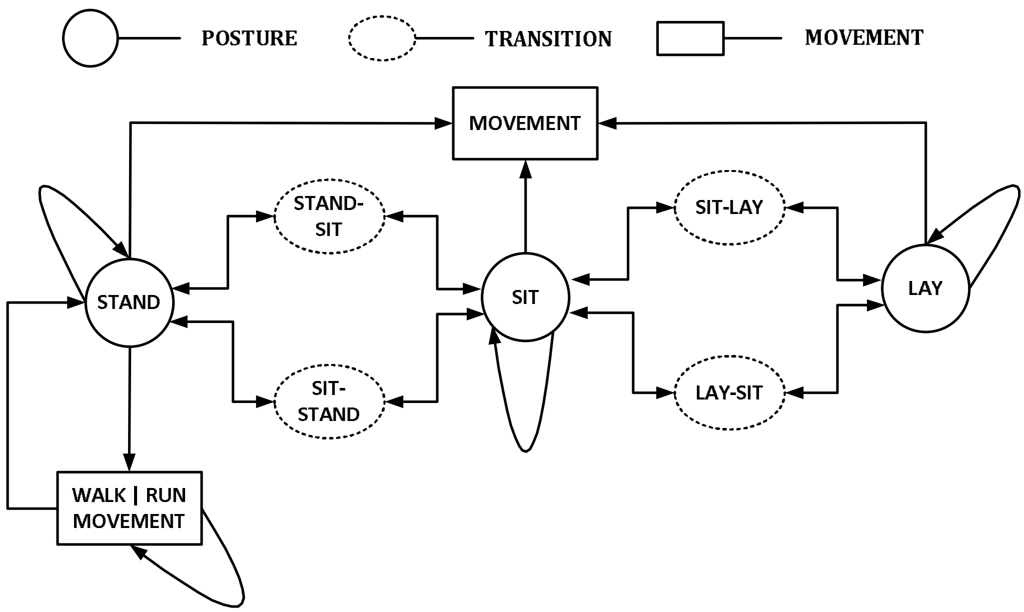


Figure 5 Physical Activity Transition Model

4.5 Feature Extraction

Initial data analysis and experimentation process of presented research showed that mean and standard deviation of the acceleration signal, being simple features, have potential to identify physical activities and transitions with reasonable accuracy. In presented work, the computed mean and standard deviation from accelerometer signal correspond to expected physical activity posture and associated movement.

4.6 Sensor Data Collection

The physical activities considered in this research study were composed of basic activities of daily life, such as standing, sitting, lying and walking, using single body-worn tri-axial accelerometer attached to subject's waist. There are various reasons why a small number of researchers have worked on the basic activities (with some exceptions, as described in Chapter 3). Recognition of these activities becomes challenging with only single accelerometer because:

(1) These activities are hard to discriminate (for example, standing and sitting) due to the similar posture pattern.

(2) This high similarity among activities is not uniform throughout the whole dataset. In simple words, a subset of activities share high similarity among its activities but are very different from another subset. For example, standing and sitting are very similar; however, they are very different from walking.

(3) In addition to long-term postures and movement, short term movements such as stand-to-sit, sit-to-stand, sit-to-lay and lay-to-sit are also part of the basic activities. These short-term activities are the most widely performed tasks that represent transition from one posture to another. These transitions play important role in physical activity recognition system because if transitions are not handled properly, they could result in large number of misclassification. Recognition of these transitions with reliable accuracy has not been successful because the features highlighted in previous systems need to be calculated over longer time-windows.

Thus the goal of this research is to develop and evaluate a classification scheme that, unlike previous systems, can recognize basic activities of daily life associated with transitional activities with reliable accuracy in real-time.

An important step towards recognizing physical activities is a collection of reliable and realistic data collection. To this end we formulated four requirements and considerations as the basis of our data recording. First, as the primary aim was the recording of basic activities, we explicitly started with the recording of these activities with annotation. Second, the recording should be as realistic as possible so the activities should be performed in naturalistic way. Third, the usefulness and the usability of activity recognition system strongly depend on the price and form-factor of the device. Therefore we decided to keep the algorithms, features and sensor-platform as simple and power efficient as possible so that embedding into a simple self-defined device is feasible in future. Forth, data recording was started with small group of healthy subjects in controlled environment, as primary aim was to analyse sensor's data among different subjects and show the feasibility of basic activities recognition first.

One requirement formulated above was to base our recognition on simple sensors and easy-to-compute features which is why mean and standard deviation of acceleration signal were chosen. Rapid advancements in Micro-electromechanical Systems (MEMS), accelerometers sensors are cheap and can easily integrated in custom-build devices. The use of simple features for recognition would allow the computation to take place in real-time on the sensor device without draining the battery.

Two different studies were done for the evaluation of the proposed algorithm. The first study was with a limited number of healthy subjects in a controlled environment. The explicit goal of this study was to analyse sensor's data and extracting features which are computationally inexpensive and more reliable. The second study with 30 elderly subjects was conducted in an uncontrolled environment.

The detailed description of experimental setup, dataset collection and evaluation results will be presented in Chapter 5.

4.7 Sensor Data Analysis

The selected feature set (mean and standard deviation, as described in Section 4.5) was computed for each PA dataset. The descriptive statistical analysis was conducted for each subject. The purpose of data analysis was to observe probability distribution of each PA dataset samples, data distribution variations among subjects in terms of features and confidence intervals.

For each PA, the dataset were constructed in the following way:

Let, $D_{PA} = \{d_1, d_2, \dots, d_n\}$ where $PA = \{STAND, SIT, WALK, LAY\}$ and n is the number of PA data samples.

Each $d_i = \{x_1, x_2, \dots, x_m\}$, where $x_i = no.of\ samples$ and m is the number of sensor raw data samples which are used to compute the features.

We analysed PA dataset, in three different perceptions, with respect to Mean (variable) and two hypothesis conditions $H_0: \mu = \mu_0$, $H_a: \mu \neq \mu_0$ with assumption of equal variances.

4.7.1 Single dataset of subject's particular activity

Motivation: Samples from a population (PA dataset) will show variation in their means. Therefore samples might have different mean when drawing two samples from a single population even though the underlying population is the same.

For example, if two samples are drawn from the same distribution. There will always be some non-zero likelihood of obtaining a difference in the means of these samples, although no difference should actually be there. We analysed three samples of different size drawn from the same population. Note that we have two samples. We can compute the difference of the means of these two samples. Because these two samples were drawn from the same distribution, their difference should be 0. But with samples of small size some differences can be observed. We computed the probability of getting non-zero differences between two samples. The results show how the size of the sample changes the probability. Moreover, the smaller the sample size the higher the probability of non-zero difference.

The Figure 6 shows the histogram of these mean differences. The blue distribution, the one generated by resampling with the smallest sample size (1) has the largest standard deviation. Therefore there is higher chance of observing a difference with a small sample size. We plot vertical lines indicating the empirical difference. The height of the distributions of the matching colour (i.e., matching sample size) at the location of the empirical difference (vertical coloured line) is the probability that the empirical difference was obtained by chance given by sample size.

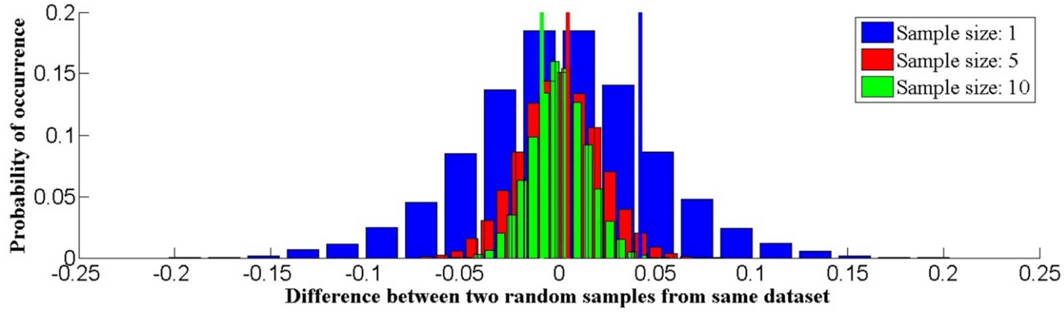


Figure 6 Probability of getting difference between two random samples as a function of sample size

4.7.2 Multiple datasets of subject's activity

Data analysis was done among multiple datasets of a particular activity from single subject. Each dataset was collected in different days to observe data distribution. Figure 7 shows the histogram of sample mean of multiple PA datasets. It is observable that, not only within single dataset, multiple datasets have significant mean variations.

PA dataset from a particular subject collected on the same day was analysed and the achieved results showed significant data variations in features; mean and standard deviation. The results suggest that, for correct PA classification, the activity recognition model cannot rely on fixed activity classification parameters. However, parameters need to be updated as subject's behaviour change.

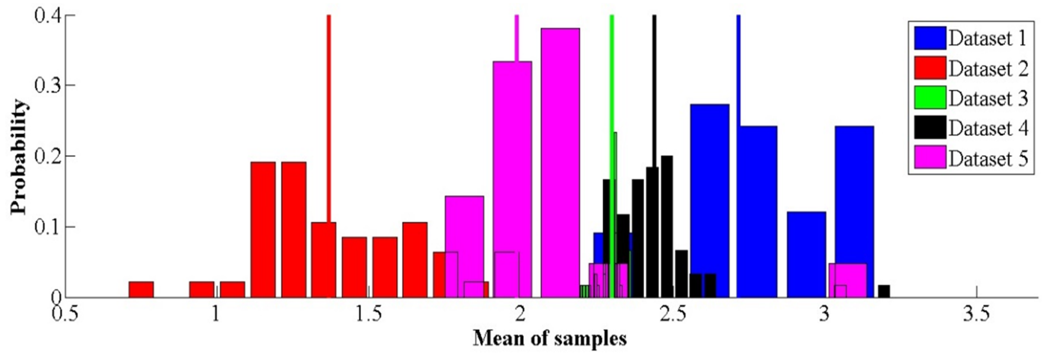


Figure 7 Probability of sample mean distribution of multiple datasets of single subject

4.7.3 Similar PA dataset of multiple subjects

An independent two-sample t-test of difference in mean with equal variance was conducted between same PA datasets of two subjects. For example, dataset of subject-A (M = 2.4357, SD = 0.1578) and subject-B (M = 2.2982, SD = 0.0336) with conditions; t (120) = 6.653 and p < 0.001 suggests that there is no similarity between datasets at α = 0.05 significance level.

Confusion matrix among random selected datasets was generated. Two output parameters; hypothesis result and associated p-Value, was analysed which clearly show non-similar likelihood among data distributions. Table 6 represents the outcome results.

Furthermore, all PA datasets samples were analysed among 5 (random selected) healthy and elderly subjects. Dataset from healthy subjects was collected in controlled situation and dataset was gathered from elderly in an uncontrolled environment. The Figure 9 shows a comparison between healthy and elderly subjects in terms of feature (mean). The results indicates that the sensor attached to the subject's waist generate different feature values in healthy and elderly. In our opinion, each PA may exhibit inter-subject variability depending upon subjects' physical characteristics; weight, height, health status etc., and intra-subject variability due to change in physical conditions, environment, and situations.

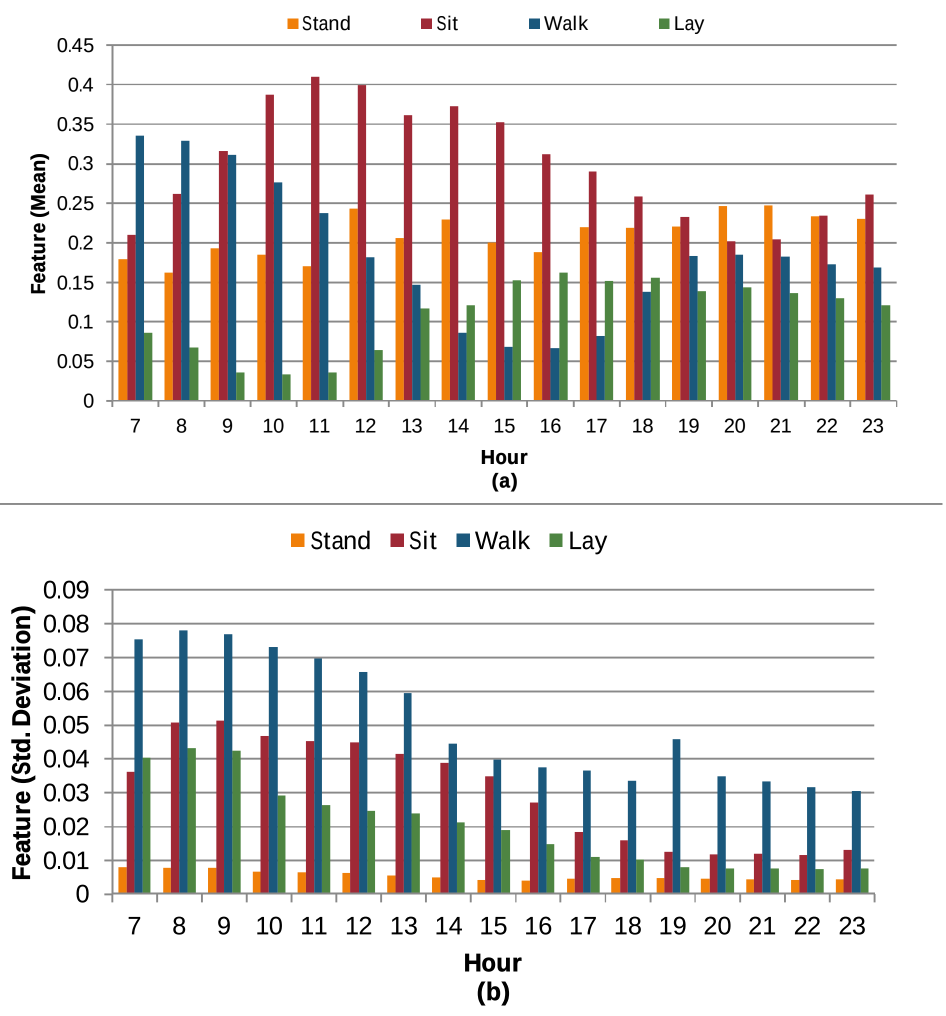


Figure 8 Intra-subject Data Variability; a) PA data variations in mean, b) PA data variations in standard deviation

Table 6 Confusion Matrix: Among selective subjects datasets

Subject	***1***	***2***	***3***	***4***	***5***
	Output: (Hypothesis result / p-Value)				
1	(0/1)	(1/0)	(1/0)	(1/3.8e^{-5})	(1/1.1e^{-5})
2	(1/0)	(0/1)	(1/0)	(1/0)	(1/0)
3	(1/0)	(1/0)	(0/1)	(1/0)	(1/1.7e^{-5})
4	(1/3.8e^{-5})	(1/0)	(1/0)	(0/1)	(1/0)

Subject	*1*	*2*	*3*	*4*	*5*
5	(1/1.1e^{-5})	(1/0)	(1/1.7e^{-5})	(1/0)	(0/1)

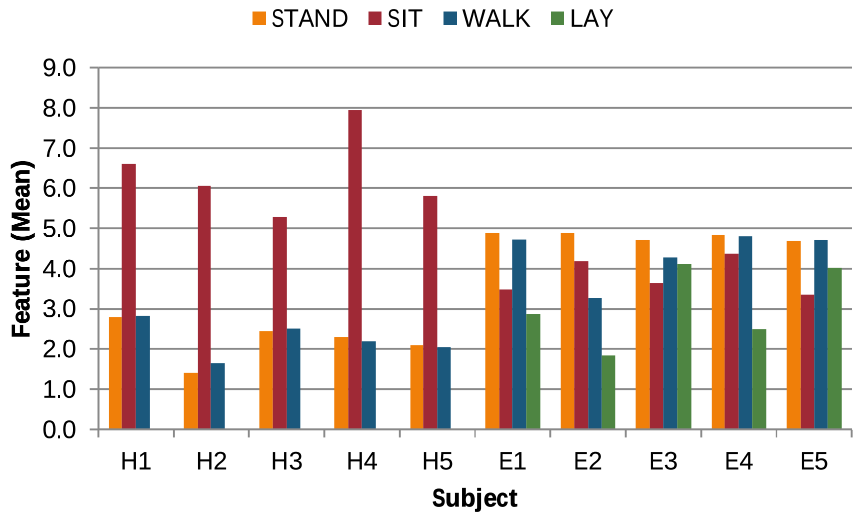


Figure 9 Inter-subject Data Variability

In conclusion, the results highlight the fact that there is significant variation in the parameters; mean and standard deviation, within single/multiple datasets of single subject and among different subject's. Thus, this parameter needs to be estimated continuously not only for one subject but for every subject. The feature parameter standard deviation which represents subject's movement associated with particular activity, could be useful in determining not only the PA associated movement but also subjects' health, change in physical activity behaviour and potential new health pathologies.

The data analysis results support the argument to develop activity recognition algorithms which are subject-dependent and truly represent physical behaviour of respective subject. Subject-dependent system will incorporate personalized activity monitoring.

4.8 Methodology

In the area of activity recognition, classification algorithms are generally categorized using fixed threshold-based methods or machine learning (ML) Techniques. These techniques are described in detail in Section 2.6.

In relation to Sensor Data Analysis (Section 4.7), designing an algorithm based on fixed parameters is not effective. This is due to variations in the population data within single/multiple subjects. Moreover in any PA there could be a possibility to observe behavioural change. Generally these behaviour changes in the activity may not be observed in daily life; however sensing device has the capability to differentiate.

Contrary to fixed threshold-based methods, ML provides classification technique and clustering method to find optimal solution in many areas. These algorithms require a training data to initialize the reasoning process which can classify data based on how the learning or training phase is done i.e. supervised learning, unsupervised learning (clustering) and semi-supervised learning. ML techniques require large amount of labelled data to achieve classification results with reliable accuracy. The traditional clustering methods are generally considered for PA classification of unlabelled data (Lee & Cho 2011)(Ugulino et al. 2012). Usually traditional clustering methods work on specific algorithm which is not sufficient to classify human activity (Zhang & Yoshie 2012). In conventional clustering methods the algorithms' objective is to partition n data points into k clusters. This is done in such a way that each data point belongs to the cluster with nearest mean (centroid). Due to inter/intra-subject data variability, applying different clustering algorithms results in different centroids for the same data. It is more likely that activities are misclassified due to unavailability of large labelled data sets for each PA to train the classifier.

The proposed methodology overcomes fixed thresholds and clustering problems with a semi-supervised subject-dependent clustering model framework. The model requires limited amount of labelled data, for training, to compute initial centroids of PA clusters. The subsequent assignment of new data samples to cluster's centroid is conditioned to a physical activity transition model.

The presented semi-supervised subject-dependent clustering model is composed of two parts;

- Statistical Model
- Semi-supervised Clustering Model

The proceeding sections explain the details behind construction and optimization of classifier design. The architectural model of classifier design is shown in Figure 10.

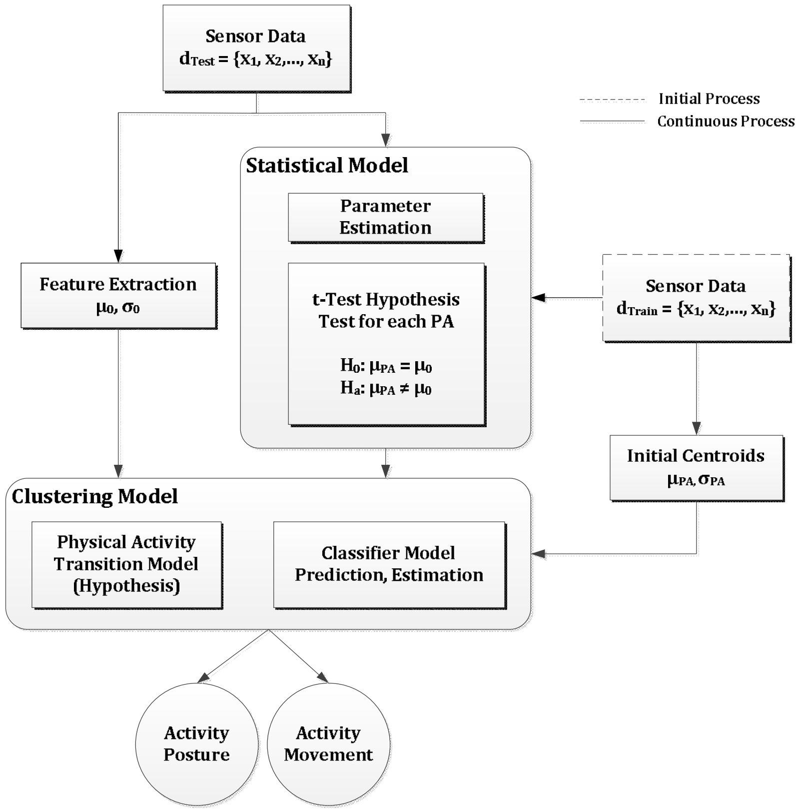


Figure 10 Architectural Model of Classifier Design

4.8.1 Training Dataset

A single accelerometer sensor was worn by subject at waist using belt. The dataset, of 8-10 minutes, consist of four physical activities (STAND, SIT, WALK and LAY) performed by the subject. Each activity was labelled during training data acquisition. Subject performed each activity in controlled situation under the supervision of observer. The subject performed the activities in the following order:

- STAND (two minute)
- STAND-to-SIT
- SIT (two minute)
- SIT-to-STAND
- STAND (two minute)
- WALK (two minute)
- SIT-to-LAY
- LAY (two minutes)
- LAY-to-SIT

Subject was requested to perform each activity in his/her normal way so sensor data reflects the true activity behaviour. The collected dataset can be considered as empirical data for the subject who is under experimentation.

The PA dataset is formalized in the following way:

Let dataset, $D_{PA} = \{d_1, d_2, \dots, d_n\}$

Where $PA = \{STAND, SIT, WALK, LAY\}$

And $d_i = \{mean, standard\ deviation\}$.

Each data sample $d_i = \{x_1, x_2, \dots, x_m\}$ was computed using $m = 20$ samples of raw acceleration data (see Section 4.2 for sensor specification). The number of samples is dependent on the sampling frequency of the accelerometer sensor.

We compute empirical mean μ_{PA} by the sample mean of D_{PA} using (1),

$$\boldsymbol{\mu_{PA} = \frac{1}{m}\sum_{i}^{m} x_i} \quad (1)$$

And, we compute empirical standard deviation σ_{PA} by the sample standard deviation using (2),

$$\boldsymbol{\sigma_{PA} = \sqrt{\frac{1}{m-1}\sum_{i}^{m}(x_i - \mu_{PA})^2}} \quad (2)$$

The confidence interval was computed using percentile method. The described training dataset collection procedure will be applied to each subject.

After collecting training dataset for each PA, the following parameters will become the input of the model which includes;

Table 7 Input parameters of classification model

Activity	***Total empirical samples***	***Feature***		***95% Confidence Bounds***
		Mean	***Std. deviation***	
STAND	2400	μ_{STAND}	σ_{STAND}	$[\mu^{L}_{STAND}, \mu^{U}_{STAND}]$
SIT	2400	μ_{SIT}	σ_{SIT}	$[\mu^{L}_{SIT}, \mu^{U}_{SIT}]$
WALK	2400	μ_{WALK}	σ_{WALK}	$[\mu^{L}_{WALK}, \mu^{U}_{WALK}]$

Activity	Total empirical samples	Feature		95% Confidence Bounds
		Mean	Std. deviation	
LAY	2400	μ_{LAY}	σ_{LAY}	$[\mu^{L}_{LAY}, \mu^{U}_{LAY}]$

4.8.2 Statistical Model

The first component of the presented model is the statistical model as shown in Figure 11. In this component, for every new observed data samples, we want to find an estimator and an $(1-\alpha)100\%$ interval for the mean μ_{PA}. The goal is to estimate sample mean μ_0 with respect to empirical mean μ_{PA}. We consider mean estimation problem as comparing two sample means; new sample mean and empirical mean, with assumption of equal variances. We use t-test (statistical method) to establish the likelihood of the equal mean of two samples. The $\alpha = 0.05$ level was used as a significance criterion.

The statistical model is composed of two sub-components;

- Parameter estimation
- Hypothesis test

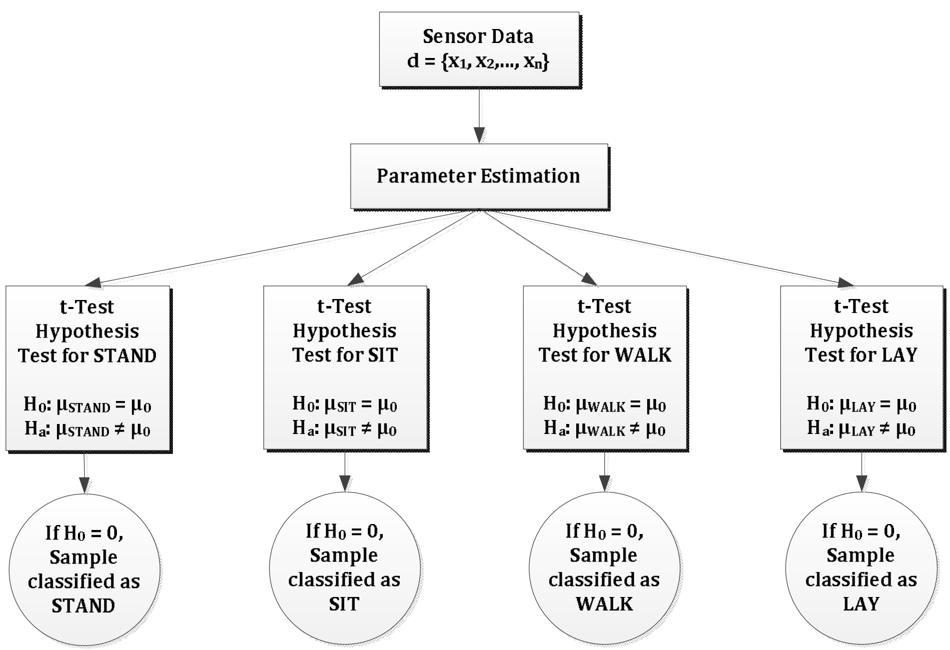


Figure 11 Statistical Model

4.8.2.1 Parameter Estimation

For each new observed data sample, let d = $\{x_1, x_2, \dots, x_m\}$ and m be an independent and identically distributed samples/sec collected from the accelerometer sensor, and suppose we wish to find an estimator and $[\alpha 100\%, (1-\alpha)100\%]$ interval for the mean.

Usually, we estimate μ_{PA} by the sample mean

$$\boldsymbol{\mu_0} = \frac{\mathbf{1}}{\boldsymbol{m}}\sum_{i}^{m} \boldsymbol{x_i}$$

A confidence interval for μ_{PA} can be found by determining the distribution of μ_0, and finding values μ_0^L, μ_0^U such that

$$\boldsymbol{P\left(\mu_0^L \geq \mu_{PA} \leq \mu_0^U\right) = 1 - \alpha}$$

4.8.2.2 Hypothesis

An independent two sample t-Test for comparing sample mean and empirical mean with assumption of equal variances was conducted.

The research hypothesis is: testing dataset samples (new observed samples) will have different mean than the empirical mean computed from training dataset.

$$H_a\colon \mu_{PA} \neq \mu_0$$

The null hypothesis would be: testing dataset samples (new observed samples) will have equal mean with empirical mean computed from training dataset.

$$H_0\colon \mu_{PA} = \mu_0$$

The above hypothesis test finds the probability that two sample means are drawn from the same data distribution. The result H_0 = 0 will indicate that t-Test does not reject the null hypothesis at α = 0.05 significance level.

Figure 12.(a) shows samples mean variation of testing dataset samples of a particular PA and computed empirical mean from training dataset and 95% confidence interval. Figure 12.(b) shows the probability distribution of samples. Figure 12.(c) shows the hypothesis test results. The hypothesis result H_0 = 0 indicates that new observed sample comes from the same PA distribution and considered as classified activity.

In following section, we provide an example for the model working demonstration. A testing dataset consist of two activities; STAND and SIT, collected from a subject was provided to the model as an input. The activity will classified based on t-test for comparing two means hypothesis.

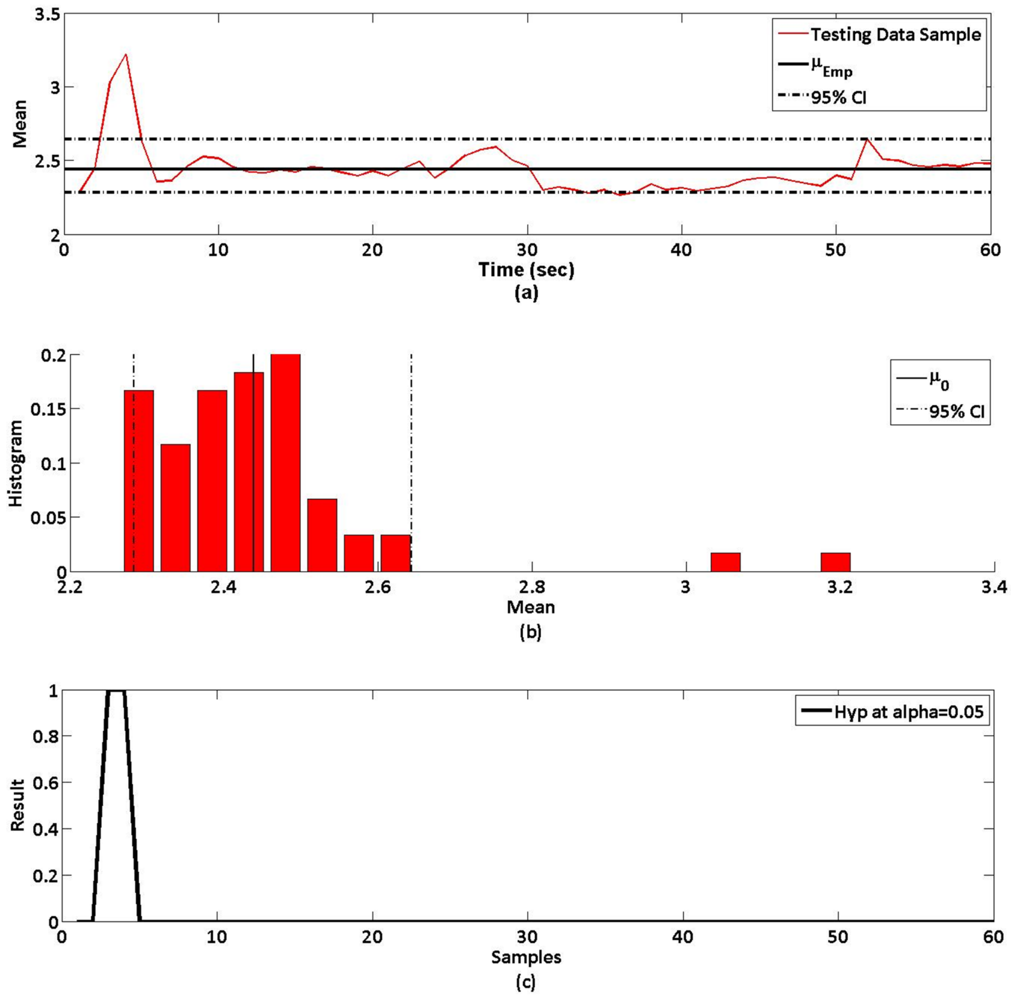
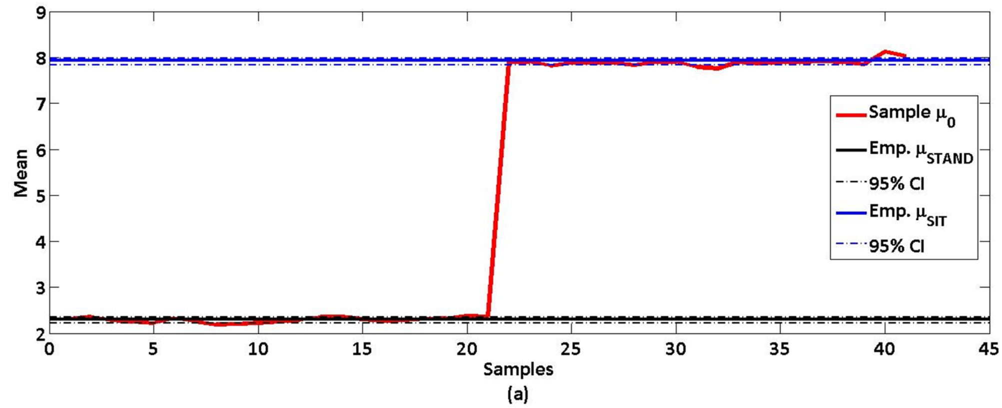


Figure 12 Testing dataset samples statistics of a particular PA, a) Sample mean $\mu_0$variation over time b) Probability distribution of samples mean μ_0. The μ_{Emp} is the empirical mean of respective PA and associated 95% confidence intervals c) Two sample t-Test hypothesis results at $\alpha = 0.05$ significance level. The result $H = 0$ indicates that test does not reject null hypothesis.

4.8.2.3 Model Demonstration Example of Two Activities

Let testing dataset $D_{Test} = \{d_1, d_2, \dots, d_n\}$ consist of two activities; STAND and SIT. The empirical means of STAND and SIT are already computed during training phase. The testing data set and empirical information of STAND and SIT with respective empirical means is shown in Figure 13.(a). For each testing sample (μ_0) $d_i = \{x_1, x_2, \dots, x_{20}\}$, the parameter mean will be estimated, as explained in Section 4.8.2.1. At this moment statistical test for testing sample against each PA training sample will be conducted at $\alpha = 0.05$ significance level, as illustrated in Figure 11. The hypothesis results are shown in Figure 13.(b).



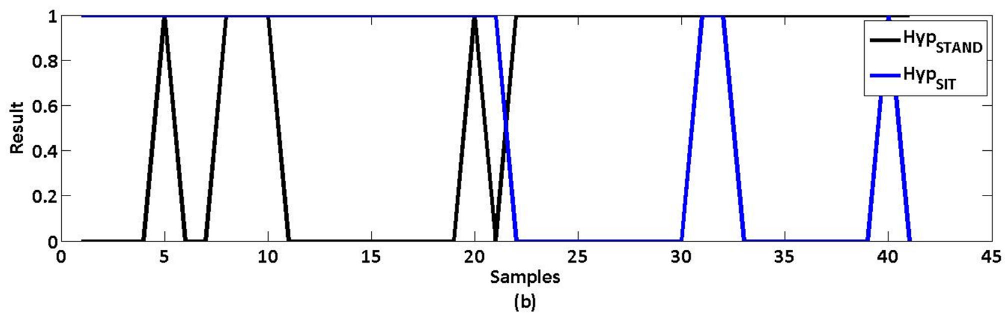


Figure 13 Statistical Model Demonstration, a) Testing dataset sample mean μ_0, empirical means of STAND and SIT from training dataset and respective 95% CI, b) PA classification based on t-test hypothesis at $\alpha = 0.05$ significance level.

Classification Results:

- The new observed samples will be classified as, for example, STAND, if t-test hypothesis test for STAND returns $\boldsymbol{H_0 = 0}$.
- It is unlikely that two or more hypothesis results generate $\boldsymbol{H_0 = 0}$, however, the only possibility is that two PA's have overlapped confidence bounds. The overlapped confidence bounds indicate that activities are having similar behaviour. For example, STAND and WALK are activities which are quite similar in terms of mean parameter, however can be discriminated in terms of standard deviation parameter as explained in Section 4.4.2. Furthermore, the mean parameters can be estimated using bootstrap technique. The bootstrap method was invented by B. Efron (Efron 1979) as an approach to calculate confidence intervals for parameters in circumstances where standard methods cannot be applied (Efron & Gong 1983). The short description of bootstrap principle is explained in Chapter 8.

- It is likely to have $\boldsymbol{H_0} = \mathbf{1}$ from more than one PA hypothesis tests. The rejection of null hypothesis indicates, in general, that observed samples have no similarity to gathered training PA data samples and need to be addressed.

In conclusion, the presented statistical model ensures the samples correct classification with 95% confidence. The subject-dependent model approach also resolves the data variability and fixed thresholds issue among subjects. Furthermore, the approach has the capability to include more physical activities and classify based on the respective PA training samples.

In the following section, the samples which statistical model could not classify, or samples which reject the null hypothesis, will be addressed. The problem, to associate new observed samples to initially collected PA training samples knowledge, was addressed with the help of machine learning (ML) techniques. The semi-supervised clustering approach is considered. The initial prior knowledge (training samples) of each PA was collected in a supervised way. Then observed samples will be classified using unsupervised k-Means clustering technique.

4.8.3 Semi-supervised Clustering Model

Most unsupervised clustering methods work with the objective to partition n data samples into k clusters in such a way that each data sample belongs to nearest mean (centroid). Each PA may exhibit inter-subject and intra-subject data variability, also observed in Sensor Data Analysis (Section 4.7), therefore different clustering algorithms end up in identifying different centroids for the same data samples.

The presented clustering model resolves random selection of centroids for clustering and needs less training data to classify PA. The model is composed of the following stages,

- Clusters' Centroid Initialization
- Classifier for Physical Activity Classification
- Unsupervised Learning

The model diagram is shown in Figure 14.

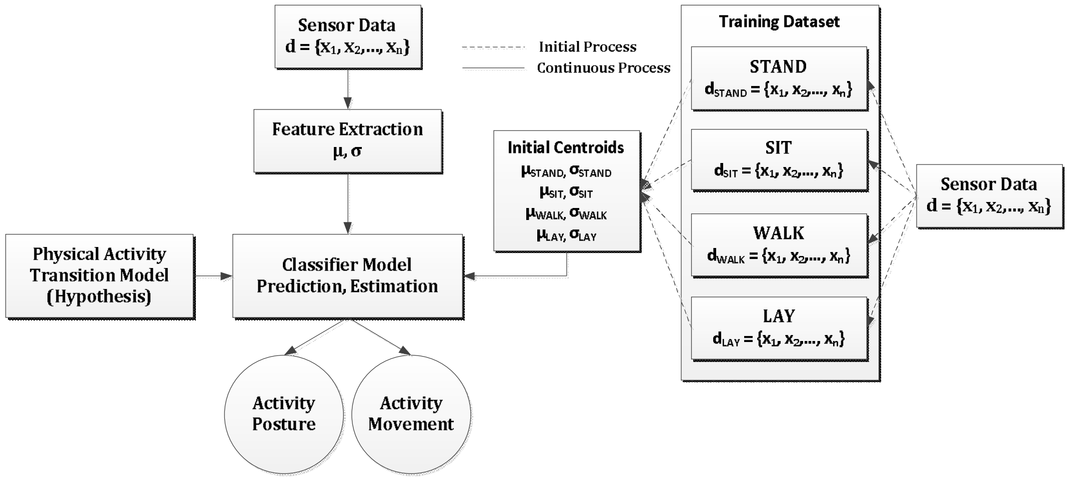


Figure 14 The Semi-supervised Clustering Model Framework

4.8.3.1 Centroids Initialization

For subjects profiling, sensor data for each physical activity: D_{PA} = $\{STAND, SIT, WALK, LAY\}$, from each subject is acquired as described in Section 4.8.1. The training dataset is considered as true representation of the subject's PA. Each training dataset corresponds to a respective PA cluster. The feature mean μ_{PA} computed for each PA cluster can be considered as true cluster centroid. The obtained train datasets are homogenous with respect to each physical activity and associated features. The major advantage of profiling is to obtain clusters' centroids which are subject-dependent and to avoid random selection of centroids by traditional algorithms.

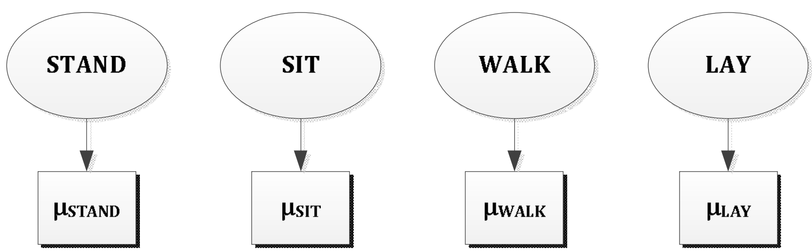


Figure 15 Clusters' Centroid Initialization Using Training Dataset

4.8.3.2 Classifier for PA Classification

In the second stage, a classifier model is defined which is composed of clustering model (Prediction) and physical activity transition model (Estimation) for associating subsequent sensors data to the correct cluster as shown in Figure 14. Each physical activity and transition was considered as states, with an assumption that initial state of the activity posture is STAND. For every new observed data samples, the features μ_0 and σ_o were computed. The new feature set values and initial centroids computed in the previous step will be the input of the classifier for activity prediction. The classifier model is shown in Figure 16.

- Prediction: Clustering model is based on traditional k-means technique which predicts the activity. Mean Squared Error (MSE) for each $\boldsymbol{D_{PA}}$ was computed using Eq. (3), to estimate the difference between predicted computed feature $\boldsymbol{\mu_0}$ and true value of the estimator $\boldsymbol{\mu_{PA}}$.

Each MSE value of physical activity is the distance from each respective PA cluster centroid (mean value). Having minimum MSE refers to minimum distance from cluster centroid, as a predicted activity.

$$\boldsymbol{MSE_{PA}} = \frac{\boldsymbol{1}}{\boldsymbol{n}} \sum_{i}^{n} (\boldsymbol{\mu_i} - \boldsymbol{\mu_{PA}})^2 \qquad (3)$$

- **Estimation:** by picking the minimum MSE, the algorithm will classify the true activity posture based on physical activity classification as described in Section 4.4.2. As a result, proposed methodology will provide posture and associated movement estimation as an output.

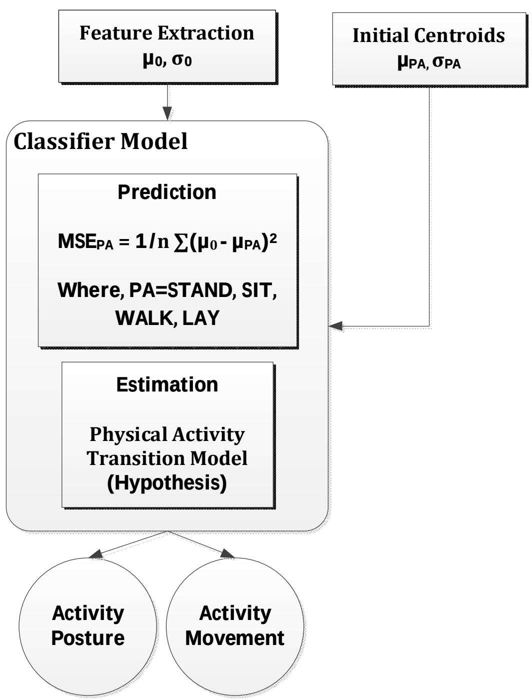


Figure 16 Classifier for PA Classification

4.8.3.3 Unsupervised Learning

In the third stage, we define a learning algorithm with a capability to recognize shifts in subjects' behavioural statuses, identification of unexpected events, and re-computation of clusters centroids of tuning physical activity features. This stage is an adaptive learning about a particular subject. The Section 5.3 will describe the situation where particular PA data samples changed their distribution from associated training data samples distribution.

4.9 Block Diagram of Proposed Machine Learning Algorithm

The physical activity recognition algorithm is developed using machine learning components: (i) Feature extraction (Input), (ii) Physical activity transition Model (Hypothesis), (iii) Classifier, (iv) PA recognition (Output), and (v) Unsupervised learning. The block diagram is shown in Figure 17.

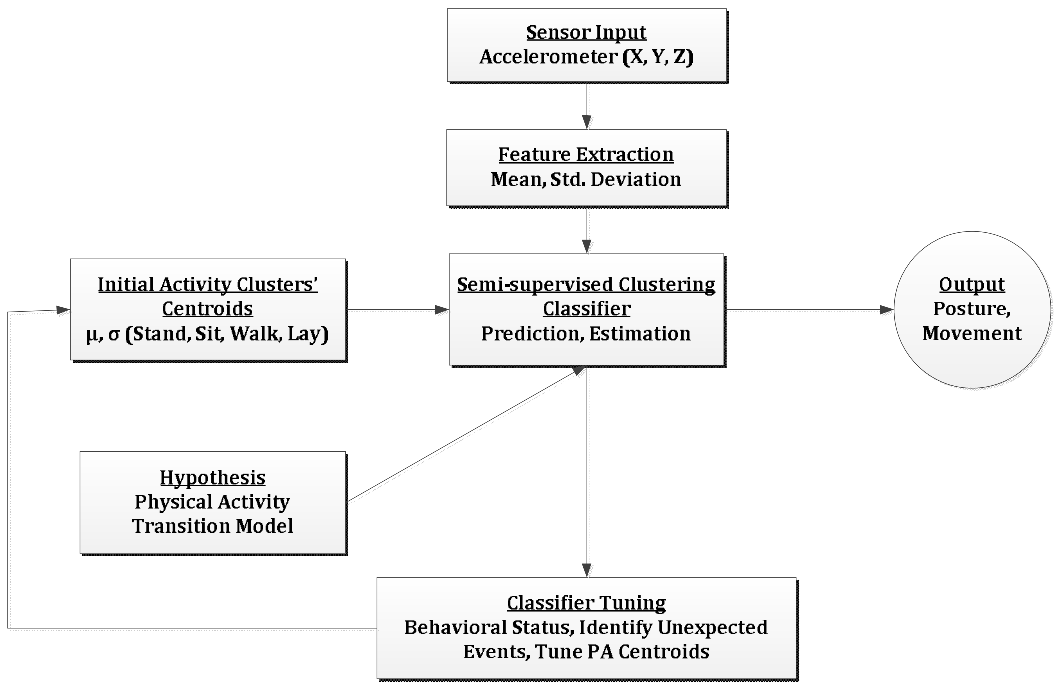


Figure 17 Block Diagram of Proposed Algorithm

In the next chapter we evaluate the presented model using two data collection experimental settings; controlled and uncontrolled.

5 EVALUATION

"Evaluation is systematic interpretation and inferring predicted or actual results."

This chapter describes in detail the evaluation of the proposed semi-supervised clustering approach using proposed feature set in controlled and uncontrolled experimental settings. It also describes the experimental settings for data collection, reasoning behind the implementation of activity classification scheme and significance of achieved results in terms of accuracy.

Two different studies were done for the evaluation of proposed algorithm. The first study was with limited number of subjects in a controlled environment. The explicit goal of this study was to analyse sensor's data and extract features which are computationally inexpensive and more reliable. The second study with 30 subjects was conducted in an uncontrolled environment.

5.1 Controlled Dataset for Model Evaluation

5.1.1 Experimental Setup

Contexta-CARE system was used in order to evaluate the proposed semi-supervised clustering approach for $PA_i = \{STAND, SIT, WALK\}$. The Contexta-CARE system, shown in Figure 18, is composed of the following components: (i) a Wireless Sensor Network (WSN) (Stankovic 2006), based on IEEE 802.15.4 protocol, called Contexta-NET (Merico 2009)(Merico et al. 2011)(Merico et al. 2013) that is used for gathering data about user and environment and (ii) an intelligent concentrator software that computes high level information about gathered data, (iii) a custom-build data acquisition network device, called Mobile Device (MD), that includes a Jennic JN5148 transceiver and a tri-axial accelerometer and A mobile phone application is used to label subjects data. The evaluation process described below has been repeated for each subject.

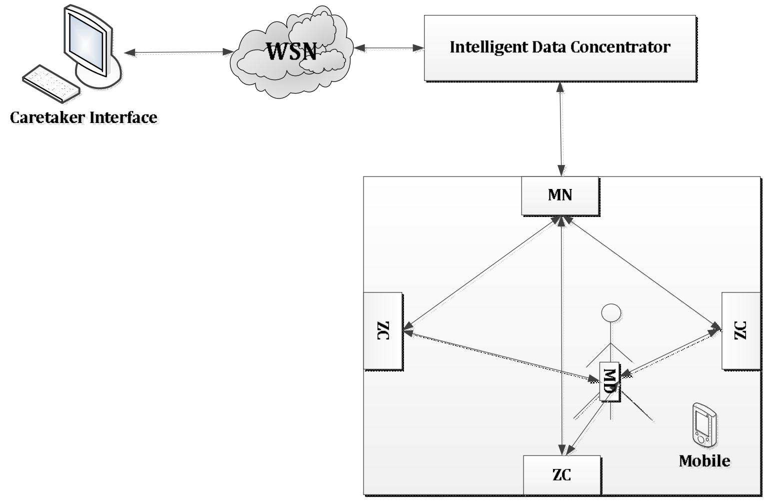


Figure 18 Contexta-CARE: Hardware architecture

The intelligent concentrator shown in Figure 19, implements multi-sensory tracking engine, is used to compute the user location, a situation assessment component, and physical activity recognition component for better understanding of the user's contextual situation that is occurring.

Particularly, the physical activity recognition component is composed of: (i) computation of Feature Extraction, (ii) Posture Manager, (iii) Movement Manager, (iv) Learning Algorithm (for tuning features with respect to physical activity), and (v) Prediction of critical situations and identification of change in user's normal activity statuses over time.

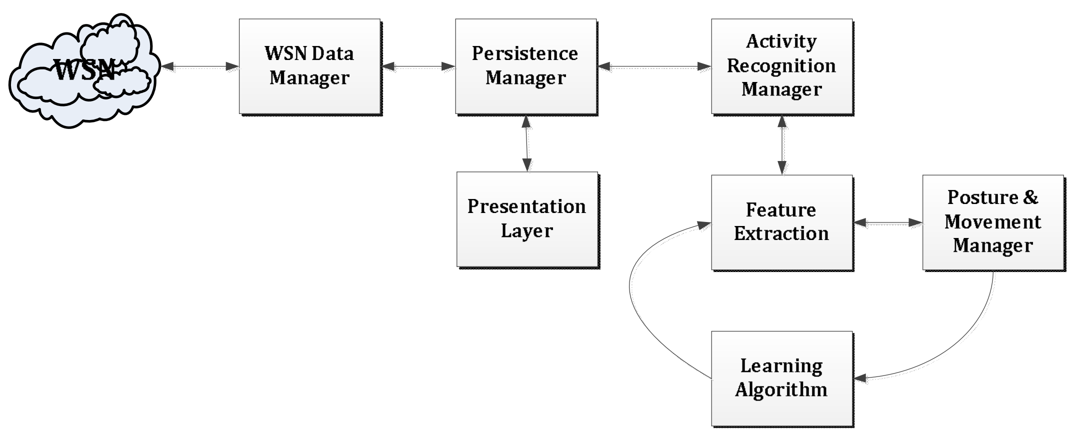


Figure 19 Contexta-CARE: Software architecture

5.1.2 Dataset Collection

The body-worn tri-axial accelerometer sensor was attached at subject's waist. The dataset were collected from 7 healthy subjects (39±12.67 years). Each dataset, of 8-10 minutes, consist of three physical activities (standing, sitting, and walking) performed by each subject. Each activity was labelled with the separate mobile application.

The data gathering activity was divided in two protocols; under observer's supervision, and without observer's supervision.

- Protocol-I: Training dataset (Standardized activity baseline test)

  In the first phase, each subject was asked to perform each activity in controlled way; under observer's supervision. Initially, the subject was in standing position with the sensor attached to the waist. Later, the subject performed the activities in the following order:

  - Standing (two minute)
  - Stand-to-sit
  - Sitting (two minute)
  - Sit-to-Stand
  - Standing (two minute)
  - Walking (two minute)

Dataset of Protocol-I has to be collected with special care otherwise it will not represent the true PA behaviour of subject.

- Protocol-II: Testing dataset (Without observer's supervision)

  In the second phase, each subject performed 4-6 min standardized sequence of standing, sitting and walking activities in uncontrolled way and subject was free to perform activities in different order. The total duration of the protocol is about 10 minutes.
  Each dataset was recorded five times on different days in order to analyse that if there was any data variation in subjects' activities.

5.1.3 Feature Extraction

The data gathered was then imported to MATLAB for further processing, where different physical behaviours (standing, sitting, walking and transitional activities) were examined. In this research study, we are not considering any specific physical motion in the side plane. We define the horizontal plane as combination of the Z-, and the X-axis which is computed by using (4).

$$\boldsymbol{ACCZX_{Horiz}} = \sqrt{\boldsymbol{AccZ^2} + \boldsymbol{AccX^2}} \quad (4)$$

For each PA, the datasets were constructed in the following way:

Let, D_{PA} = $\{d_1, d_2, \dots, d_n\}$ where PA = $\{STAND, SIT, WALK, LAY\}$ and n is the number of PA data samples.

Each d_i = $\{x_1, x_2, \dots, x_m\}$, where $x_i = no.of\ samples$ and m is the number of sensor raw data samples which are used to compute the features.

For each d_i, the features (mean and standard deviation) which were computed from accelerometer raw data signals at sampling frequency of 20 Hz with one second window.

The computed mean will be used to identify expected PA postural and standard deviation as associated PA movement.

5.1.4 Evaluation Results

In this section, we describe the evaluation procedure and results of basic life activities; standing, sitting, walking and transitional activities, using presented approach as explained in Section 4.8. We will first report the results achieved by applying statistical model for feature/parameter estimation and then show how classification performance can be improved by proposed semi-supervised clustering model. The evaluation procedure reported below was applied to each subject individually.

5.1.4.1 Training Dataset Collection

The training data recordings shown in Figure 20 contains activities; stand, sit and walk respectively. The figure shows the raw signal, which is the magnitude of the acceleration occurring at the waist, sampled at 20 Hz. The 2 minute activity data of each PA is concatenated in the figure.

Let dataset D_{PA} = $\{d_1, d_2, \dots, d_n\}$, where n no. of samples and PA = $\{STAND, SIT, WALK\}$, represent samples of a particular subject PA collected using Protocol-I (as described in Section 5.1.2). Each sample d_i is combination of two parameters; mean and standard deviation as explained in Section 5.1.3. With an assumption of true PA representation, the dataset was considered as empirical data. We computed two statistics for the dataset; mean μ_{PA} and standard deviation σ_{PA}. The 95% confidence interval was computed using percentile method. The descriptive statistics is shown in the Table 8.

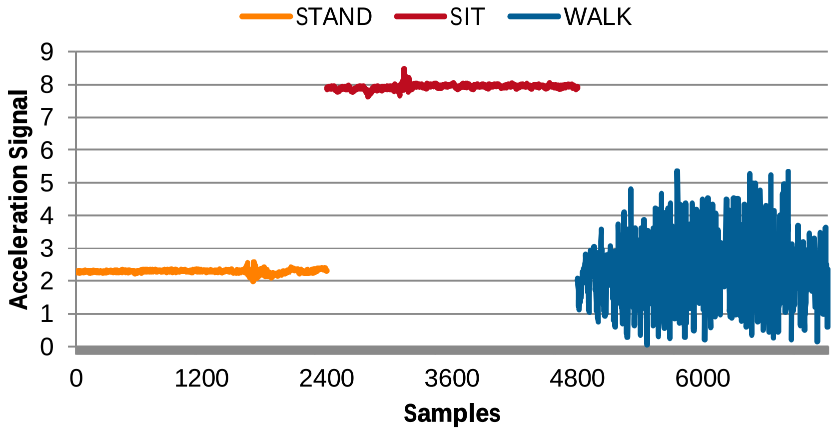


Figure 20 Accelerometer signal variation over planes.

Table 8 Descriptive statistics of PA Training data.

Activity	*Stand*	*Sit*	*Walk*
Mean	2.2983	7.9321	2.1855
Std. Deviation	0.0294	0.0362	0.7796
95% CI	[2.2230, 2.3559]	[7.8306, 7.9750]	[1.6213, 2.6918]

5.1.4.2 Statistical Parameter Estimation

Let dataset $D_{Test} = \{x_1, x_2, \ldots, x_n\}$ represent samples of the same subject's PA collected using Protocol-II (as described in Section 5.1.2). For each sample mean x_i, the estimated parameter mean μ_0 was computed using Eq. (5), and hypothesis test was conducted.

$$\boldsymbol{\mu_0 = \frac{1}{n}\sum_{i}^{n} x_i} \tag{5}$$

The estimated parameter confidence bounds, using Eq. (6), were computed using two-sided Student-t distribution.

$$\boldsymbol{\mu_{Est} = \mu_0 \pm t_{\alpha/2}\left[\frac{s}{\sqrt{n}}\right]} \tag{6}$$

We consider mean estimation problem as comparing two sample means; one empirical mean (μ_{PA}, as a result of training data) and new sample mean μ_0, with assumption of equal variances. We use t-test (statistical method) to establish the likelihood of the equal mean of two samples from unknown distribution. The α = 0.05 level was used as a significance criterion. The presented results describes the parameter estimation for single activity, however same approach was applied to other activities.

Figure 21 shows the distribution of sample mean, estimated mean with reference to empirical mean. The red dotted lines represent the 95% confidence interval of empirical mean.

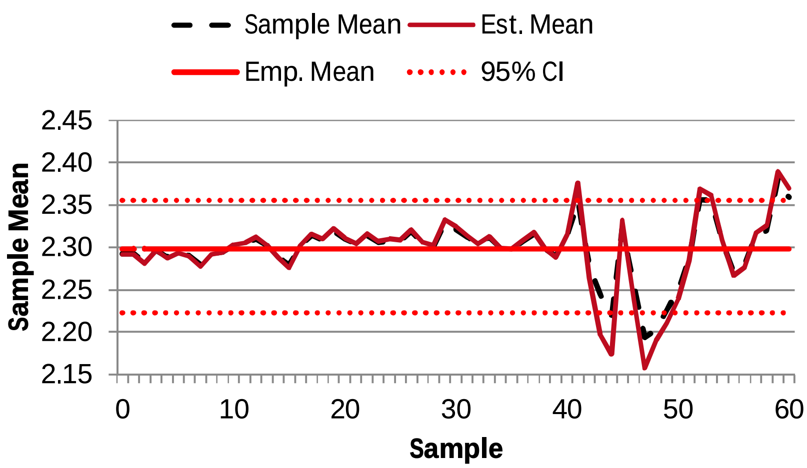


Figure 21 Parameter estimation of the mean

Interpretation

A t-test finds the probability that the two means were drawn from the same distribution. The p-Value, sample probability occurrences, helps to decide whether or not to reject null hypothesis. The significance level was set at 0.05. If the probability $p < 0.05$, we can reject the null hypothesis; which means that samples are not identified as correct PA. The samples will be considered as correctly classified if $p > 0.05$. The two-sample t-test hypothesis results are represented in Figure 22.

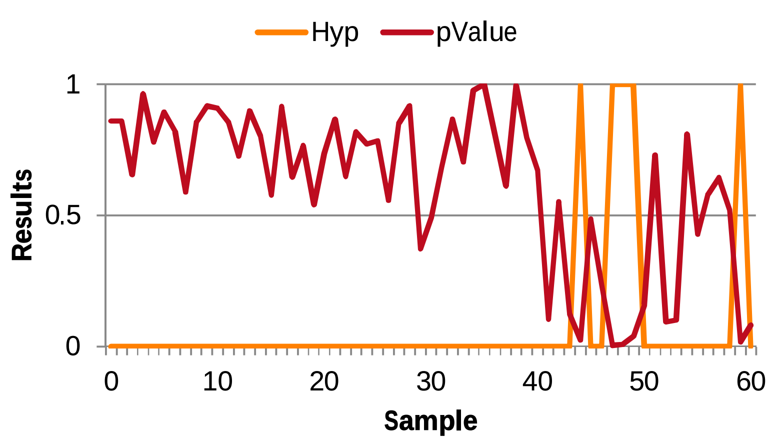


Figure 22 Hypothesis Results

Error Estimation

The standard error of the mean (i.e., of using the sample mean as a method of estimating the population mean) is the standard deviation of those sample means over all possible samples (of a given size) drawn from the population. Standard Error (SE) of the means was calculated using Eq. (7). Error margin was set based on empirical dataset which was considered as true dataset of particular PA.

$$SE_{Est} = SE_{Emp} - SE_{Sample} \tag{7}$$

The results shown in Figure 23 reflect the standard deviation in the sampling distribution of the statistic (mean).

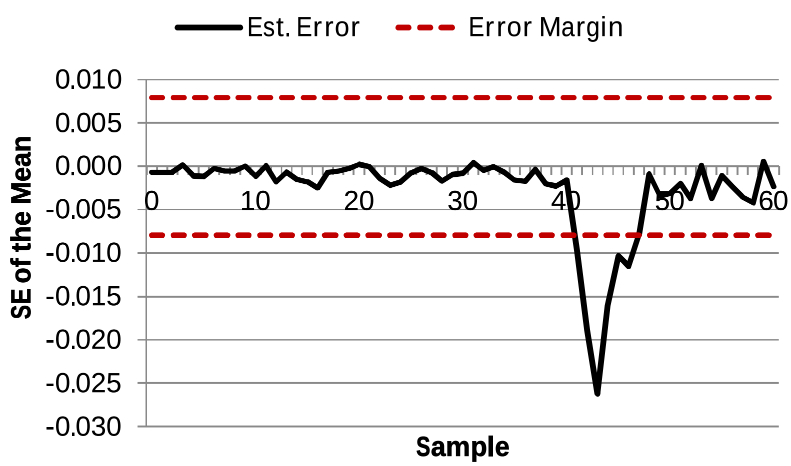


Figure 23 Error estimation results between empirical and sample mean

5.1.4.3 Classification using Statistical Model

We performed classification of the testing dataset, based on the statistical t-test hypothesis, using empirical parameters computed from training dataset for each PA. When comparing to the ground truth to the hypothesis results, the achieved PA classification is shown in Table 9.

Table 9 PA Classification using Statistical Model

Activity	***Classified Samples (%)***	***Misclassified Sample (%)***
Stand	91.67	8.33
Sit	95.0	5.00
Walk	98.3	1.70

The achieved results with statistical model are based on one parameter μ_{PA}. The testing samples which were classified with 95% confidence are shown as classified samples in the above table. The samples below 95% confidence are shown as misclassified samples. The misclassified testing dataset samples will be addressed by semi-supervised clustering model in the following section.

5.1.4.4 Semi-supervised Clustering Model

Figure 24 shows the same D_{Test}, under evaluation, with sample mean (μ_i) and standard deviation (σ_i) over time frame. The empirical parameters for PAs (μ_{PA}) are represented as μ_{STAND}, μ_{SIT} and μ_{WALK}. In order to avoid wrong initialization of cluster centroids, the presented approach initialize clusters' centroid with empirical parameters acquired using D_{Train} (training dataset) in supervised way (described in Section 4.8.3). We call PA cluster centroid initialization process as prior knowledge.

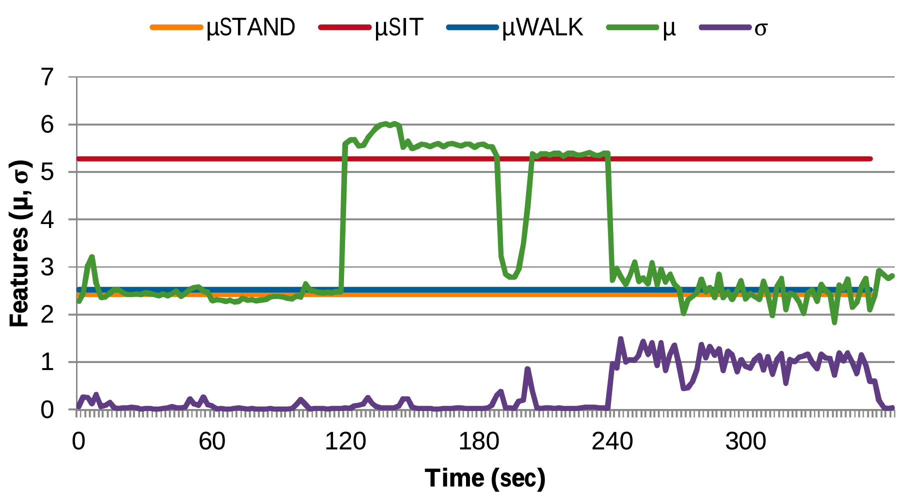


Figure 24 PA clusters' centroids (μ_{STAND}, μ_{SIT} and μ_{WALK}) acquired using supervised way and variations in test sample features/parameters μ, σ while performing PA in unsupervised way.

After acquiring prior knowledge, for each new D_{Test} (testing dataset) sample mean (μ_i), Mean Squared Error (MSE) was computed to estimate the difference between predicted computed feature/parameter μ_i and true value of the estimator μ_{PA}, where $PA = \{STAND, SIT, WALK\}$. The MSE was calculated using Eq. (8).

$$\boldsymbol{MSE_i} = \frac{1}{n}\sum_i^n(\boldsymbol{\mu_i} - \boldsymbol{\mu_{PA}})^2 \text{ where } n\text{=20 samples/sec} \qquad (8)$$

Each MSE value of PA is the distance from each respective cluster mean centroid (μ_{PA}). Having minimum MSE refers to minimum distance from cluster centroid, as predicted activity. By picking the minimum MSE, the algorithm will classify the true activity Posture (as shown in Figure 25) based on the physical activity transition model as described in Section 4.4.2.

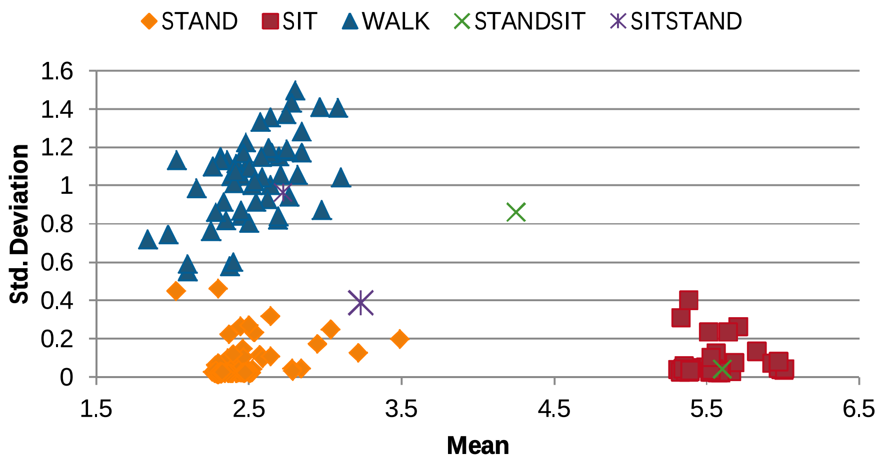


Figure 25 PA Classification using Physical Activity Transition Model

Figure 26 shows final output of the model where the True PA (in black colour) as the ground truth and Estimated PA (in red colour) as the PA classified by the semi-supervised clustering technique. Moreover, the clustering model identifies the transitions among different PAs.

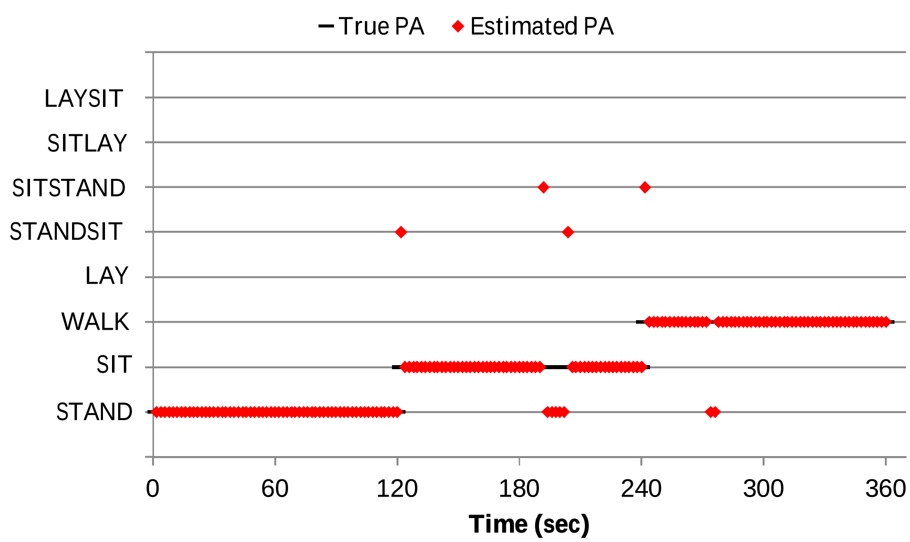


Figure 26 Estimated PA using Semi-supervised Clustering Model

5.1.4.5 Classification using Clustering Model

The results shown in Figure 26 are represented in Table 10, as confusion matrix among activities and transitions. The training datasets do not contain sample data for transitions; however, the clustering model is capable of detecting transitions between two activities based on Physical Activity Transition Model (which is described in 4.4.2). Moreover in the case of Walk activity, there are some samples which are classified as Stand is due to the fact that the presented approach discriminates these two activities with respect to associated movement (std. deviation).

Table 10 Controlled Dataset: PA Confusion matrix and classification results

Activity	*Stand*	*Sit*	*Walk*	*Trans.*	*Accuracy (%)*	*Error Rate (%)*
Stand	2400	0	0	0	100.00	0.00%
Sit	0	2360	0	40	98.33	1.67
Walk	60	0	2320	20	96.67	3.33
Subject's PA Recognition Accuracy					98.33	1.67

In conclusion, the error rate generated by statistical model for activities; STAND and SIT were 8.33, 5.00 respectively were improved by clustering model to 0.00 and 1.67. Moreover during transitional phase, the samples classified as transitional activity are considered as misclassified. Furthermore, the error rate for WALK increased from 1.50 to 3.33. The reason behind this is that the clustering model discriminates STAND from WALK not only with mean but also with standard deviation. Thus, if there is no significant movement, in terms of standard deviation, in WALK samples then the model will classify these samples as STAND.

5.1.5 Controlled dataset: PA Classification Results

Table 11 shows the classification accuracy achieved of each healthy subject, which participated in the laboratory experimentation. The average accuracy achieved from 7 subjects was about 93.77(±4.49)% on average.

Table 11 Controlled dataset: PA Classification Results

Subject	*Accuracy (%)*	*Error Rate (%)*
Subject: 1	87.99	12.01
Subject: 2	93.19	6.81
Subject: 3	98.33	1.67
Subject: 4	97.22	2.78
Subject: 5	88.38	11.62

Subject	*Accuracy (%)*	*Error Rate (%)*
Subject: 6	98.67	1.33
Subject: 7	92.60	7.4
Overall Recognition Accuracy	93.77±4.49	6.23

5.2 Uncontrolled dataset for Model Evaluation

5.2.1 Experimental Setup

The second study was conducted with group of 30 elderly of (72.69 ± 1.46) years. The group consist of 13 males of (M = 72.44, SD = 1.33) years, 17 females of(M = 72.88, SD = 1.56)years in which 7 subjects had previous fall history. The inclusion criteria for both groups are as follows:

- Home-dwelling
- Able to move around without walking aids
- Able to take verbal instructions on movements

Inclusion criteria for the functional fit group are:

- Able to walk 500 m without walking aids
- Preferred gait speed ≥ 1.1 m/sec

Inclusion criteria for the functional impaired group are:

- Preferred gait speed < 1.1 m/sec

Participants were recruited from seniors' citizen centres in the municipality of Trondheim, Norway and from exercise groups for seniors with impaired physical function.

5.2.2 Dataset Collection

The dataset was collected using commercially available body-worn accelerometer sensor in unsupervised way, as described in Section 4.2.2. The sensing device was attached to the waist of the subject. Each dataset, of 7-14 days, consist of recordings of the physical activities; STAND, SIT, WALK and LAY, performed by each subject. All activities were labelled by sensing device with already defined classification algorithm. The labelled data was used for presented approach evaluation and validation purposes.

5.2.3 Data Analysis and Feature Extraction

The data gathered was imported to MATLAB for further processing and analysis, where presented activity recognition algorithm was used to identify the physical activities: standing, sitting, walk and lying, and walking and transitions between these activities.

In order to apply the presented approach, where training dataset consist of true representation of under evaluation physical activities was extracted from each dataset of each subject. The same approach as explained in Section 5.1.3 was applied in the construction of training and testing datasets for each subject.

5.2.4 Evaluation Results

The training data recorded shown in Figure 27 consist of representation of accelerometer signal acquired for physical activities. Each dataset contains 10 min of respective PA performed in unsupervised way.

Let training dataset samples $D_{PA} = \{d_1, d_2, \dots, d_n\}$, where n no. of samples and $PA = \{STAND, SIT, WALK, LAY\}$, represent samples of a particular subject PA. Each sample d_i is combination of two parameters; mean and standard deviation as explained in Section 5.1.3. The training dataset was considered an empirical data representation of each PA. We computed two statistics for the dataset; mean μ_{PA} and standard deviation σ_{PA}. The 95% confidence interval was computed using percentile method.

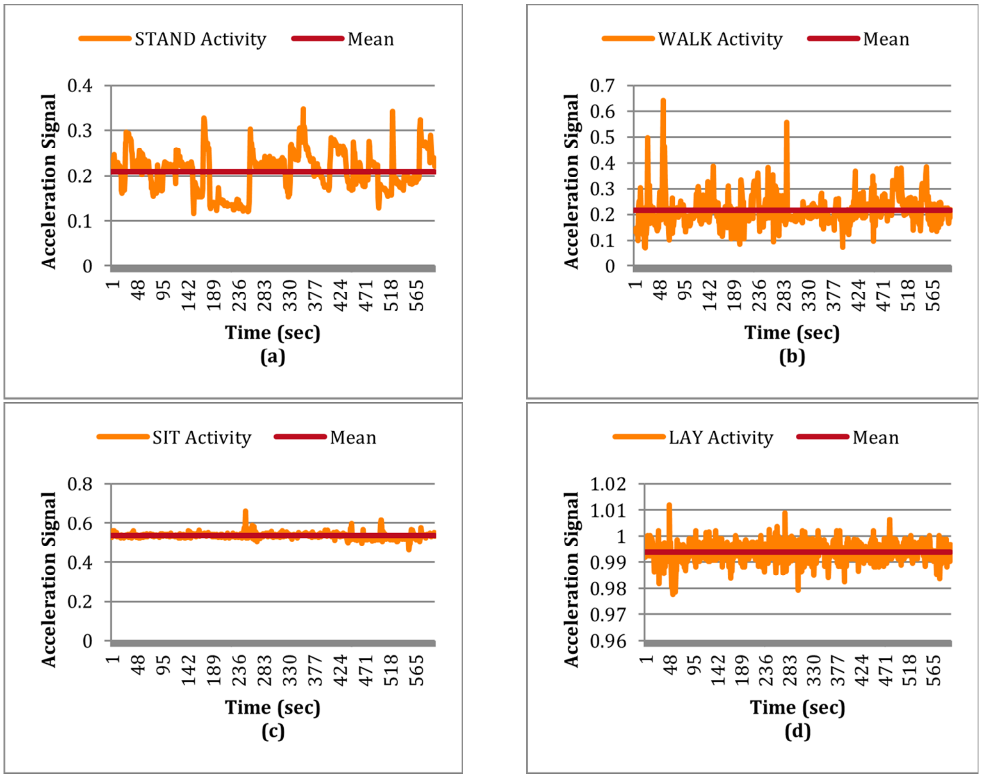


Figure 27 Acceleration signal of training dataset. a) Stand activity with mean (μ_{STAND}), b) Stand activity with mean (μ_{WALK}), c) Stand activity with mean (μ_{SIT}), d) Stand activity with mean (μ_{LAY})

The descriptive statistics is shown in Table 12.

Table 12 Descriptive Statistics

Activity	*Descriptive Statistics*		
	Mean	**Std. Deviation**	**95% CI**
STAND	0.1957	0.0484	[0.1221,0.2743]
WALK	0.2158	0.0593	[0.1352, 0.3150]
SIT	0.5357	0.0145	[0.5149, 0.5569]
LAY	0.9939	0.0040	[0.9875, 0.999]

In order to show the evaluation results, testing dataset was extracted from the original dataset which replicate the scenario; standing, walking, sitting and lying. The total duration of the activities was 50 min. Classification of the testing dataset was performed based on the statistical t-test hypothesis using empirical parameters computed from training dataset for each PA. The hypothesis test was conducted with $\alpha = 0.05$ level of significance. When comparing to the ground truth to the hypothesis results, the achieved PA classification accuracy is shown in Table 13. Testing dataset samples that were false rejected by null hypothesis will be addressed by semi-supervised clustering model in the following section.

Table 13 PA Classification using Statistical Model

Activity	***Accuracy (%)***	***Error Rate (%)***
Stand	97.4773	2.5227
Sit	95.8403	4.1597
Walk	95.8403	4.1597
Lay	94.6755	5.3245

Figure 28 shows the same D_{Test}, under evaluation, with sample mean (μ_i) and standard deviation (σ_i) over time frame. The empirical parameters for PAs (μ_{PA}) are represented as μ_{STAND}, μ_{SIT}, μ_{WALK} and μ_{LAY}. The clusters' centroids were initialized (prior knowledge) with empirical parameters acquired using D_{Train} (training dataset).

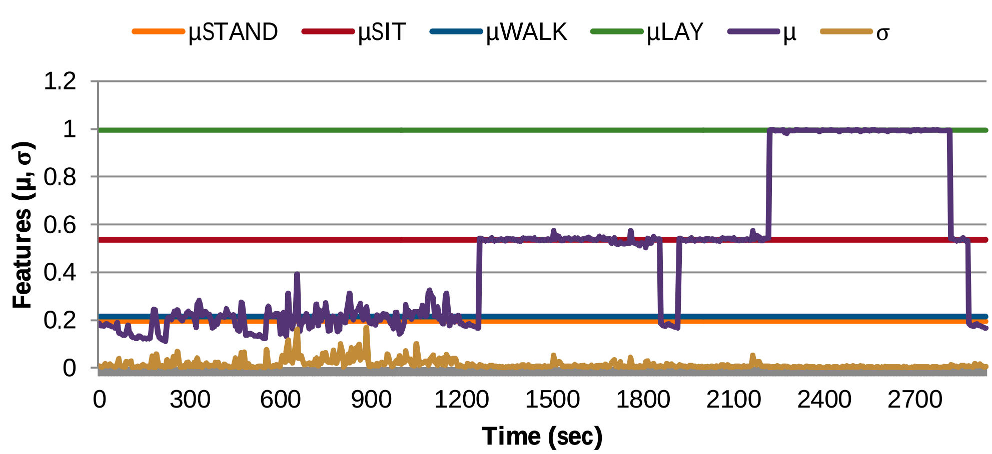


Figure 28 PA cluster centroids μ_{STAND},μ_{SIT}, μ_{WALK} and μ_{LAY} and variations in features/parameters μ_i, σ_i while performing PA in unsupervised way.

After acquiring prior knowledge, for each new D_{Test} (testing dataset) sample mean (μ_i), Mean Squared Error (MSE) was computed to estimate the difference between predicted computed feature/parameter μ_i and true value of the estimator μ_{PA}, where $PA = \{STAND, SIT, WALK, LAY\}$. The MSE was calculated using Eq. (9).

$$\boldsymbol{MSE_i} = \frac{1}{n}\sum_i^n(\boldsymbol{\mu_i} - \boldsymbol{\mu_{PA}})^2 \textbf{ where } \boldsymbol{n}\textbf{=30 samples/sec} \qquad (9)$$

By picking the minimum MSE, the algorithm will classify the true activity Posture (as shown in Figure 29) based on the physical activity transition model as described in Section 4.4.2. Figure 30 shows final output of the model where the True PA (in black colour) as the ground truth and Estimated PA (in red colour) as the PA classified by the semi-supervised clustering technique. Moreover, the clustering model identifies the transitions among different PAs.

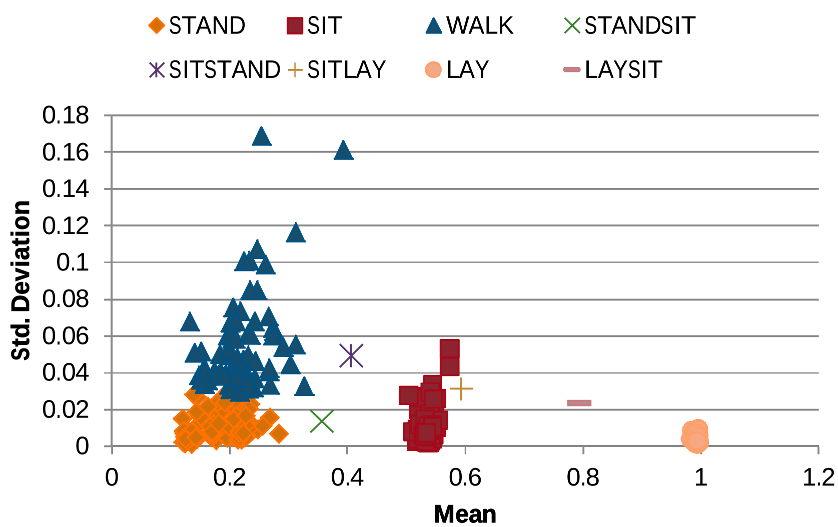


Figure 29 PA Classification using Physical Activity Transition Model.

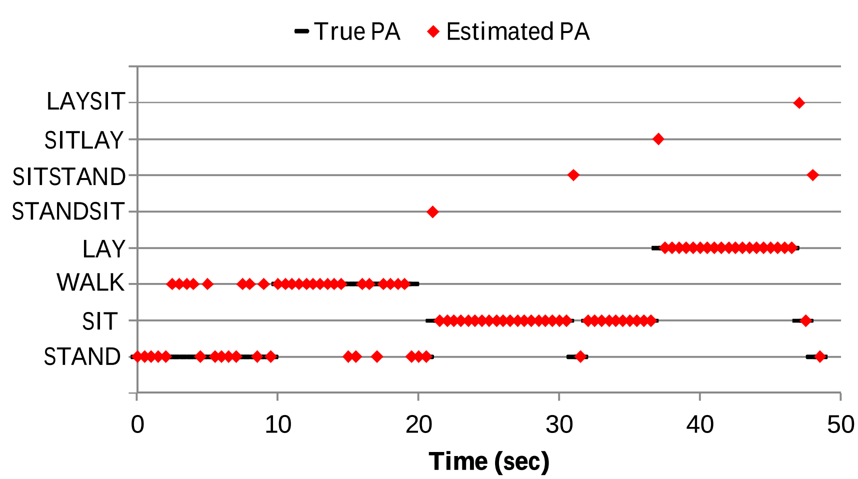


Figure 30 Estimated PA using Semi-supervised Clustering Technique

The results presented in Figure 30 are shown in Table 14 as confusion matrix among physical activities and achieved classification accuracy.

Table 14 Uncontrolled Dataset: PA Confusion matrix and classification results.

Activity	*Stand*	*Sit*	*Walk*	*Lay*	*Trans.*	*Accuracy (%)*	*Error Rate (%)*
Stand	24300	0	2700	0	0	90	10
Sit	0	17850	0	0	150	100	0
Walk	2400	0	15600	0	0	87	13
lay	0	0	0	17850	150	100	0
Subject's PA Recognition Accuracy						94	6

5.2.5 Uncontrolled dataset: PA Classification Accuracy

The dataset of physical activities; STAND, SIT, WALK and LAY, collected in unsupervised way from group consist of 13 males of $(M = 72.44, SD = 1.33)$years, 17 females of$(M = 72.88, SD = 1.56)$years was evaluated with the presented methodology. The average classification accuracy of 90.81($\pm$3.24)% was achieved.

Table 15 shows the classification accuracy achieved of each elderly subject with demographic information, which were participated in the experimentation.

Table 15 Uncontrolled Dataset: PA Classification Results

No.	*Subject ID*	*Gender*	*Age*	*Fall History*	*Accuracy (%)*	*Error Rate (%)*
1	5	2	72.70	0	90.88	9.12
2	26	1	71.59	0	95.31	4.69
3	38	2	72.58	0	89.57	10.43
4	58	2	74.82	1	85.50	14.5
5	61	2	73.55	0	92.32	7.68

No.	Subject ID	Gender	Age	Fall History	Accuracy (%)	Error Rate (%)
6	66	2	72.41	1	89.77	10.23
7	71	2	74.42	2	91.61	8.39
8	73	2	74.33	0	90.31	9.69
9	83	1	71.47	0	88.36	11.64
10	89	2	70.47	0	88.94	11.06
11	107	1	73.32	2	94.81	5.19
12	111	2	73.39	2	93.23	6.77
13	121	2	73.23	0	95.02	4.98
14	140	1	74.37	0	92.76	7.24
15	151	2	71.30	0	85.67	14.33
16	173	2	69.94	1	88.73	11.27
17	188	2	74.80	0	87.53	12.47
18	194	2	72.11	0	90.81	9.19
19	208	1	71.61	0	87.05	12.95
20	209	2	70.71	3	83.21	16.79
21	221	1	71.68	0	95.38	4.62
22	233	2	73.57	0	89.64	10.36
23	245	1	70.85	0	88.21	11.79
24	423	1	72.60	3	89.87	10.13
25	721	2	74.68	0	90.85	9.15

No.	Subject ID	Gender	Age	Fall History	Accuracy (%)	Error Rate (%)
26	769	1	74.54	0	95.75	8.17
27	771	1	74.41	0	92.81	7.19
28	783	1	72.72	0	91.83	6.21
29	811	1	71.33	0	93.79	5.23
30	812	1	71.20	0	94.77	4.25
Overall Recognition Accuracy			72.69		90.81±3.24	9.19

5.3 PA Behavioural Shift Indicators and Parameters Retuning

Mean as an indicator

We made an argument in the Section 4.7.2 that there is a possibility that subject may perform a particular same PA in different ways. As a consequence, the sensing device generates different set of data. To validate this argument, we observed a scenario as shown in Figure 31.

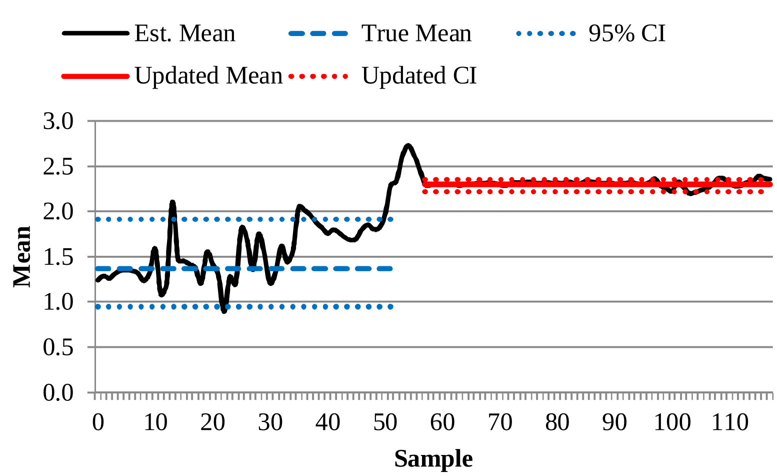


Figure 31 PA behavioural shift and parameter retuning.

The p-Value was used as an indicator for any change in the sample mean and the empirical mean. As long as the computed p>0.05, the under observation PA is within the empirical CI. In case of $p<0.05$ for certain number of samples, readjustment of parameters is needed. In our approach, we readjusted the parameters if 10 sec of consecutive samples are misclassified as any defined PA. The empirical mean information of the PA which has smaller MSE with respect to other empirical PA means was updated. The Figure 33 shows 1) estimated sample mean (in black colour) of accelerometer signal, 2) initial empirical true mean (in blue colour) which is computed from training dataset and 95% CI of empirical mean (in blue dotted colour), and 3) updated mean (in red colour) and new 95% CI of updated mean (in red dotted colour).

Standard Deviation as an indicator

Each PA has some significant amount of movement which can easily be monitored with the standard deviation parameter as shown in Figure 34. In case of no movement wither device is stationary or subject; wearing the device, may have some unexpected event. In our approach, model also keep track of the movement factor and generate an activity signal impulse every 20 sec which identifies subjects continuous PA.

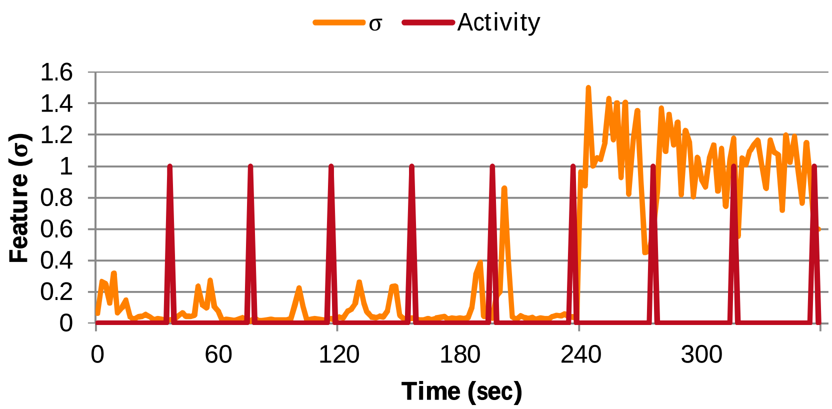


Figure 32 **Physical activity signal (condition if σ > 0.005)**

The mean and standard deviation can be good indicator of subjects' health statues in terms of physical fitness.

5.4 Comparison: Healthy and Elderly Subjects PA Datasets

We analysed healthy and elderly subjects in controlled and uncontrolled environments with respect to parameters; mean and standard deviation. The PA behavioural analysis between two healthy subjects and between healthy and elderly subject was conducted. The results shown in Table 16 suggest that there is no similarity among two independent healthy and elderly subjects in terms of mean and standard deviation.

Table 16 PA Behavioural Analysis Results

<table>
<tr><th colspan="2">Activity / Subject</th><th colspan="3">Healthy vs Healthy</th><th colspan="3">Healthy vs Elderly</th></tr>
<tr><td rowspan="8">Stand</td><td rowspan="2"></td><td>Mean</td><td>2.4458</td><td>2.2965</td><td>Mean</td><td>2.2966</td><td>0.1957</td></tr>
<tr><td>Std.</td><td>0.1896</td><td>0.0437</td><td>Std.</td><td>0.0437</td><td>0.0572</td></tr>
<tr><td rowspan="2">Levenes's Test for Equality of Variances</td><td colspan="2">F</td><td>15.703</td><td colspan="2">F</td><td>20.048</td></tr>
<tr><td colspan="2">Sig.</td><td>0</td><td colspan="2">Sig.</td><td>0</td></tr>
<tr><td rowspan="3">t-Test for Equality of Means</td><td colspan="2">t</td><td>5.942</td><td colspan="2">t</td><td>279.083</td></tr>
<tr><td colspan="2">df</td><td>118</td><td colspan="2">df</td><td>959</td></tr>
<tr><td colspan="2">Sig. (2-tailed)</td><td>0</td><td colspan="2">Sig. (2-tailed)</td><td>0</td></tr>
<tr><td rowspan="8">Sit</td><td rowspan="2"></td><td>Mean</td><td>5.2705</td><td>7.9329</td><td>Mean</td><td>7.9329</td><td>0.5357</td></tr>
<tr><td>Std.</td><td>0.8352</td><td>0.0710</td><td>Std.</td><td>0.0710</td><td>0.1717</td></tr>
<tr><td rowspan="2">Levenes's Test for Equality of Variances</td><td colspan="2">F</td><td>29.5239</td><td colspan="2">F</td><td>174.221</td></tr>
<tr><td colspan="2">Sig.</td><td>0</td><td colspan="2">Sig.</td><td>0</td></tr>
<tr><td rowspan="3">t-Test for Equality of Means</td><td colspan="2">t</td><td>-24.604</td><td colspan="2">t</td><td>2035.769</td></tr>
<tr><td colspan="2">df</td><td>118</td><td colspan="2">df</td><td>659</td></tr>
<tr><td colspan="2">Sig. (2-tailed)</td><td>0</td><td colspan="2">Sig. (2-tailed)</td><td>0</td></tr>
<tr><td rowspan="8">Walk</td><td rowspan="2"></td><td>Mean</td><td>2.5490</td><td>2.1948</td><td>Mean</td><td>2.1948</td><td>0.4679</td></tr>
<tr><td>Std.</td><td>0.4872</td><td>0.4679</td><td>Std.</td><td>0.2158</td><td>0.0701</td></tr>
<tr><td rowspan="2">Levenes's Test for Equality of Variances</td><td colspan="2">F</td><td>0.015</td><td colspan="2">F</td><td>842.395</td></tr>
<tr><td colspan="2">Sig.</td><td>0.902</td><td colspan="2">Sig.</td><td>0</td></tr>
<tr><td rowspan="3">t-Test for Equality of Means</td><td colspan="2">t</td><td>4.061</td><td colspan="2">t</td><td>94.199</td></tr>
<tr><td colspan="2">df</td><td>118</td><td colspan="2">df</td><td>659</td></tr>
<tr><td colspan="2">Sig. (2-tailed)</td><td>0</td><td colspan="2">Sig. (2-tailed)</td><td>0</td></tr>
<tr><td>Lay</td><td></td><td>Mean</td><td>-</td><td>-</td><td>Mean</td><td>2.3987</td><td>0.9938</td></tr>
</table>

Activity / Subject		Healthy vs Healthy			Healthy vs Elderly		
		Std.	-	-	Std.	0.6213	0.0047
	Levenes's Test for Equality of Variances	F		-	F	2179.758	
		Sig.		-	Sig.	0	
	t-Test for Equality of Means	t		-	t	59.6	
		df		-	df	606	
		Sig. (2-tailed)		-	Sig. (2-tailed)	0	

6 CONCLUSIONS

The following chapter summarizes the main findings and contributions in the area of physical activity recognition systems.

A brief overview of the literature in human activity monitoring was provided. The thesis explored different aspects and components of developing a robust and reliable physical activity recognition system. The thesis highlighted the fact that the success of an activity recognition system lies in four components; activity, context, subject and sensor. A single sensor is not capable of recognizing every human activity, while many sensors on the subject body are not feasible. Choice of number of sensors depends on the context and purpose of use of the recognition system.

In this thesis work, a single accelerometer sensor was attached to the subject's waist for collection of activity data. The basic activities of daily life; stand, sit, walk and lying were considered to be recognized. These basic activities are meaningful and provide enough information using a single accelerometer sensor in long-term unsupervised care of elderly/patients. The data analysis indicated that there is inter-subject and intra-subject data variability in performing activities, thus subject-independent algorithm development is not appropriate. The human body has different response times while performing the same physical activities of daily life and different subjects may have different way of performing activities. Thus, subject-dependent activity recognition is more useful and personalized. The simple features mean and standard deviation; extracted from single accelerometer sensor, have enough capability to discriminate one activity from another.

The thesis addressed the limitations of threshold-based methods and machine learning techniques and presented a methodology with the combination of threshold-based and machine learning methods. In order to avoid fixed thresholds, a simple statistical model was presented which is subject-dependent–model adapts for each individual subject. Each activity data samples were collected as the prior knowledge of the subject. The assumption was made that respective activity data samples corresponds to the true activity behaviour of the subject, otherwise the recognition system results will not be true. The model has the capability to classify activity with the 95% confidence accurately. Moreover, the model has the capability to adapt the subject's activity behaviour change. In unsupervised situations reducing the classifier training time and the amount of labelled data is important, as collecting labelled data is not possible. The novel semi-supervised clustering framework was described which need no training data, besides the prior activity knowledge, and no further offline data analysis is required. Each new subsequent sensor data will be classified with reasonable accuracy with the presented classifier using the physical activity transition model. The presented methodology can effectively classify the selected activities and transitional activities with reasonable accuracy. The indicated classification accuracy results reflect the correct recognition of stand, sit, walk and lay activities, where the transitions among these activities were considered as unclassified. As mentioned in Section 4.3 that the stand activity could include some movement, therefore in the achieved findings there are some stand samples were classified as walk and vice versa. The reason behind is of elderly's slow activity response (in terms of sensor data) found in walk and stand activities.

Most of the published work is based on findings from controlled situations. In order to validate the recognition system accuracy in both environments, two different studies in both a controlled laboratory and in an uncontrolled situation was included in the presented work. The accuracy achieved in the controlled environment (laboratory) with 7 healthy subjects was 93.77% and the accuracy achieved in uncontrolled environment (hospital) with 30 elderly subjects was 90.81%.

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8 APPENDICES

APPENDIX-I: PUBLICATIONS

1. **Hashim Ali**, Enza Messina, Roberto Bisiani. “Subject-Dependent Physical Activity Recognition Model Framework with a Semi-supervised Clustering Approach”, IEEE European Modelling Symposium (EMS), November 2013.
2. D. Merico, **H. Ali**, R. Bisiani, "Contexta-CARE: A Situation-Aware Independent-Living System", in ForItAAL 2012, IV Italian Forum on Ambient Assisted Living, Parma, Italy, October 2012.
3. D. Merico, R. Bisiani, **H. Ali**. "Reti di sensori a supporto dell'Assisted Living". Automazione e Strumentazione, March 2012.
4. D. Merico, **H. Ali**, R. Bisiani, “VoroLoc : Location Estimation Using Particle Filters , Voronoi Graphs and Ambient Sensor Data”, IPIN 2012.