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Identification and classification of motor activities using inertial sensors data

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Abstract

Activity of daily living (ADL) recognition has great importance in the field of rehabilitation, physical monitoring and ubiquitous computing. Recognition of ADL is essential because of the connection between physical inactivity and common health problems, like osteoporosis, cardiovascular disease, diabetes, obesity. This study is motivated by the fact that it is important to monitor the activities of a person in daily routines, so as to associate the day-by-day motor performance with the recommendations given by the physicians. A set of aerobic activities (walking, stairs walking, running, sitting, standing) which are considered useful to promote the well-being of a person are used to design the activity recognition system.

Inertial measurement units including accelerometer and gyroscope represent a promising technology in long term physical activity monitoring. This work aims to design a physical activity recognition system intended to classify motor activities from an inertial sensor, which can be profitably used in real-time applications. To achieve this goal, the system is designed and evaluated on different parameters of the algorithm: pre-processing steps involved in signal processing, segmentation of the signal to minimize delays associated with further processing, determination of the best feature set for classification, and training of the classification scheme based on both subject-dependent and subject-independent validation to maximize recognition accuracy. It is believed that the accuracy of systems able to recognize daily living activities in real time heavily depends on the processing steps for signal segmentation. This study presented a modified event-based segmentation algorithm that introduces a much reduced temporal delay between activity occurrence and its detection and recognition.

The system is capable of distinguishing those activities which are considered hard to differentiate in the previous studies, such as walking, stairs ascending and stairs descending. The presented scheme is not only capable to classify these activities, but it can also be helpful in ambulatory gait analysis, where on-time processing may be needed, and spaces for motion capture systems are not at hand. Finally, the availability of the inertial data flows coming from mobile phones and smart bracelets makes it possible to include the detection and recognition

algorithms presented in this thesis into these commodities, thus expanding their use also for daily living activity long term monitoring for fitness, active ageing, and “active growing” applications.

KEYWORDS: Inertial sensor, Physical activity recognition, Gait-event detection, Segmentation, Machine learning, Classification, Real-time processing.

Publications

International Journal Papers

[1] **B. Fida**, I. Bernabucci, D. Bibbo, S. Conforto and M. Schmid, "Pre-processing effect on the accuracy of event-based activity segmentation and classification through inertial sensors," S*ensors*, vol. 15, no. 9, 23095-23109, 2015.

[2] **B. Fida**, I. Bernabucci, D. Bibbo, S. Conforto and M. Schmid, "Varying behavior of different window sizes on the classification of static and dynamic physical activities from a single accelerometer," *Med Eng Phys,* vol. 37, no. 7, 705-711, 2015.

International Conference Papers

[3] **B. Fida**, D. Bibbo, I. Bernabucci, A. Proto, S. Conforto, and Maurizio Schmid, "Real time event-based segmentation to classify locomotion activities through a single inertial sensor," *Proceedings of the 5th EAI International Conference on Wireless Mobile Communication and Healthcare*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2015.

[4] **B. Fida**, I. Bernabucci, D. Bibbo, S. Conforto, A. Proto, and M. Schmid, "The Effect of Window Length on the Classification of Dynamic Activities through a Single Accelerometer," *Proceedings of the IASTED International Conference Biomedical Engineering (BioMed), Zurich, Switzerland*. Vol. 2325. 2014

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[6] B. D'Elia, **B. Fida**, I. Bernabucci, S. Conforto, T. D'Alessio, and M. Schmid, "The influence of haptic feedback on hand movement regularity in elderly adults," *ECCE '13 Proceedings of the 31st European Conference on Cognitive Ergonomics*, Toulouse, france: August 25-28, 2013.

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List of Abbreviations

Abbreviation	Meaning
ADL	Activity of Daily Living
DT	Decision Tree
EC	End Contact
FFT	Fast Fourier Transform
FS	Feature Set
GPS	Global Positioning Systems
IC	Initial Contact
IMU	Inertial Measurement Unit
k-NN	K-Nearest Neighbor
LFFS	Linear Forward Feature Selection
MEMS	Micro-Electro-Mechanical Systems
MLP	Multilayer Perceptron
MS	Mid-Swing
NB	Naïve Bayes
NN	Neural Network
PD	Parkinson’s Disease
SA	Stairs Ascending
SAD	Same Amount Of Data
SD	Stairs Descending

SFFS	Sequential Forward Feature Selection
SVM	Support Vector Machine
SVM-FS	Support Vector Machine Based Feature Selection
TC	Terminal Contact
WEKA	Waikato Environment For Knowledge Analysis

1
Introduction

1.1 Motivation

Activity of daily living (ADL) recognition has been an active area of research, with applications ranging from medicine to education and sociology and to sport analysis, and its improving trend is associated with advancements in the area of ubiquitous computing and machine learning. Among the application fields, healthcare, assistance and wellness are possibly the areas that can most profitably take advantage from research in the area of human behavior monitoring, in view of the necessity to improve healthcare by promoting different forms of active behavior, including outdoor exercising [1] and changing lifestyle [2]. In this field, ICT is already playing a major role, developing tools to detect falls [3], to measure postural adjustments [4] and to monitor mobility activities [5] [6].

There are various recommendations about physical active daily life style. According to the Haskell et al [7] recommendation statement, to promote and maintain health, all healthy adults aged 18 65 yr need moderate-intensity aerobic physical activity for a minimum of 30 min on five days each week or vigorous-intensity aerobic activity for a minimum of 30 min on five days each week or vigorous-intensity aerobic activity for a minimum of 20 min on three days each week. Also, combinations of moderate- and vigorous-intensity activity can be performed to meet this recommendation." A list of light, moderate and vigorous activities is also presented in the study. Apart from these recommendations, physicians could also recommend some exercise plan to the patients. However, it is important to monitor the activities of the person in daily routine, so as to associate the performance with the recommendations. This is the main motivation of this work, focusing on recognizing the daily living activities including aerobic activities. For the sake of availability and easiness, I focused on those daily living activities that are more important in terms of energy expenditure, thus walking, stairs walking and running were included, along with postural activities that are frequent in daily life, such as standing and sitting. Therefore, this thesis deals with the recognition of these activities which are essential for health monitoring.

Automatic recognition of activities is a crucial task in the area of assisted living and healthcare, as it involves the system to sense, learn and interpret the human behavior in real time. In terms of technology, video-based sensors to wearable sensors based approaches have been deployed. Video [8] and environmental sensor-based systems [9] work well in a controlled environment, and do not need devices to be worn by a person – thus making them very useful in surveillance applications. While, wearable sensors including accelerometers and gyroscopes have received the highest attention in this area, when long term and personal monitoring is sought: when combined together in an inertial sensor unit, they can be used to automatically and robustly recognize the activities in both laboratory and home settings.

In this study a single inertial sensor comprising one tri-axial accelerometer and one tri-axial gyroscope is used to recognize the mentioned activities. In the following, the term inertial sensor word will be used to denote units including a combination of accelerometers and gyroscopes.

1.2 Challenges in activity recognition

Automatic recognition of daily living activities from inertial sensors data is a challenging research area. When dealing with a physical activity recognition problem, several challenges exists which may significantly affect the complexity of the recognition system, such as; the number of sensors and their location on the body, number and types of activities and data collection. Following are the factors which contribute to the complexity of the recognition system:

Number of sensors: Using a small number of sensors makes a system more feasible for the long time daily living monitoring. Moreover, it also aids to the lower computational requirements. However, small number of sensors may decrease the system accuracy as compared to the larger number of sensors, due to the reduction in available information.

Location of sensors: signals coming from the inertial sensors depend on their location over the body, and can vary among different positions. Choice of the sensor position over the body should be acceptable for the long-term monitoring and still be able to generate high recognition accuracy.

Number of activities: A good recognition system should be the one which can recognize the numerous numbers of daily living activities. Recognizing a small number of activities is easier than recognizing a large number of activities, as a fact, increase in the number of activities makes harder for the classifier to discriminate among them.

Types of activities: Recognizing the static activities like sitting and standing is easier than the dynamic activities, which involves the movement of the limbs such as walking and running. Also the transitions between the sitting and standing are difficult to discriminate. Moreover, activities which share similar pattern during movement are hard to recognize, such as walking, stairs ascending and stairs descending.

Data collected for the activities: Data collection is a crucial step in the designing of the activity recognition system. The algorithm which is trained on the laboratory restrict data might be failed to recognize activities over the data collected during free living conditions. In the laboratory conditions activities are performed with same speed and limited amount of time, while in free living conditions participants might perform activities differently. Unsupervised monitoring is the one way to collect the data with fewer restrictions, inside or outside the lab. This might face some challenges:

- Under such settings, subjects perform activities without researcher's supervision. This might cause unreliable labeling of the data, which leads to degrade the system accuracy.
- As subject has to perform activities in his/her own manner, this might lead to variability in movement patterns among the subjects. For example, one person can walk on stairs at slow speed, whereas other can walk fast and this could become hard for the algorithm to categorize the activity.

1.3 Limitations of Previous Systems

In a number of studies, automatic activity recognition is usually performed through multiple inertial sensors attached at different locations of the body [10]-[16]. Though recognition is higher in this case, carrying multiple sensors on the body may not be advisable if easiness of use is pursued [17]. The studies in which only one accelerometer is suggested have pointed out the waist/sternum location as the best location for activity detection [18]-[21], but there is a variation in the accuracy results, among different activities.

- Most of the previous studies have excluded the transitions (i.e. dynamic activities that are associated with the change of a steady motor activity or posture, such as sit-to-stand acts ,gait initiations/termination, first and last steps on stairs, direction changes when walking) to minimize data misclassifications [11] [13] [22] [23]. Such systems have produced good classification accuracy even if the small size of time window is used to segment the signal, as the fact of data generalization.
- In the case of locomotion activities, most of the studies have used fixed length time window to segment the data, lengths lie in the range (1-10) s [11] [15] [24] [25] [26], and the presence of overlapping between consecutive windows is usually limited to 50%. One limitation of this approach is that problems can arise if an activity lasts for shorter or longer time periods than the pre-defined window length.
- Moreover, studies have suggested that removing noise from the accelerometer and gyroscope signals can enhance the classification accuracy of the system [27]-[30] and

segmentation of the gait patterns [31] [32] [33] [34] respectively. While it increases the complexity of the system for online applications: if the filtering used is composed of just two taps, at least 2 × (1000/sampling frequency) milliseconds will be needed as the waiting time, to have the preceding samples available for the processing.

- Additionally, an ideal activity classification system should work off-the-shelf. In other words, it should be able to use the data from a range of previous subjects to identify activities from an unseen individual. However, most of the times this is not possible and an intra-subject classification scheme is currently all that can be achieved for some problems. With this approach, sample training data are required for a given individual before classification can be performed. Although the literature supports the fact that accelerometry has emerged as an effective and inexpensive mean to recognize physical activities, little work has been done to validate the idea under unsupervised real-world circumstances. Majority of the prior work on physical activity recognition using acceleration signals relies on the data collected in supervised controlled laboratory settings. The studies have shown high success in recognizing the most prevalent everyday physical activities, such as sitting, lying, walking and running. However, when tested for long-term out-of-lab monitoring the recognition accuracy of these systems decreased significantly.

1.4 Study Goal

An efficient physical activity recognition system using body-worn inertial sensors should be composed of some main requirements.

(1) The system should recognize activities in real-time. This means that the need of preprocessing steps including inclination removal and noise removal should be checked, if it has no significant effect on the recognition accuracy then it might be excluded as its presence could contribute to the system complexity. Moreover, selection of segmentation technique must avoid delay response; it could be a short time window length or dynamic window which works in real time. Finally, the extracted features and classification algorithms should be simple, light-weight and computationally inexpensive to be able to support real time applications. (2) The

number of sensors attached on the body must be fewer, preferably one. (3) The recognition system should be robust. It should perform well on the new subjects, without doing training again. This is very challenging as people perform the same activities differently, thus huge amount of variations could exist in their activity patterns. (4) Lastly, variations in the activity patterns should not affect the classification accuracy of the recognition system. This is also very hard to achieve as humans can perform the same activities in infinite different ways and it is difficult to collect enough training data to fulfill this need.

The aim of this study was to implement a physical activity recognition system by using single inertial sensor. The system efficiently segments the inertial sensor data based on dynamic segmentation technique without any delay time which is faced in fixed length window based segmentation. It provides the best solution for real-time implementation. Both supervised and unsupervised data collection methods are used to validate the system, in order to keep variations among inter and intra subjects.

1.5 Contributions

This section briefly highlights the study contributions presented in chapter 5 of the thesis.

Section 5.1 addresses the neglected point of window length choice for the segmentation of the static and dynamic activities and also its impact on the recognition. Furthermore, the effect of the subject-dependent (with different percentage splits of training and testing data) and subject-independent learning is also evaluated on different machine learning classifiers.

Section 5.2 addresses the use of event-based segmentation technique for the classification of locomotor activities. A modification to a standard gait segmentation criterion is done in such a way that no window is used to detect the events of the physical activities. In this way, we are able to also evaluate the effect of a event-based segmentation on the ability to classify human physical activities (that were not limited to level walking, but included stair negotiation). Subject independent evaluation is take in to account, where algorithm is trained on one dataset and validation is performed on another dataset. This section also analyses and compares the classification accuracy obtained through an event-based segmentation against different fixed window lengths, on the classification of daily living activities. Additionally, a benchmark dataset (PAMAP2) has been also used to validate the event-based segmentation technique. Different features sets were also used to compare their performance on activity recognition. This chapter describes how dynamic segmentation could be a choice for an efficient and effective recognition system.

Section 5.3 investigates whether, and to what extent, de-noising and inclination correction pre-processing has an effect on the event-based segmentation of activities and on the subsequent classification accuracy. In particular, since the goal is to assist the researcher in building real-time applications, the monitored pre-processing operations will be considered, taking into account the computational complexity associated with their implementation.

Section 5.4 compares the different feature selection techniques and classification schemes with respect to their processing time on the daily living activities.

1.6 Thesis outline

This thesis is organized in to six different chapters (see Figure 1-1 for Dissertation schema). This chapter has presented the motivation of the research work in the field of activity recognition, challenges faced in this field and lists the contributions of this work. The rest of the thesis is organized as follow:

Chapter 2: gives an overview of the related work in the area of the activity recognition, a brief description of the sensing technologies used in the activity recognition systems, applications which have been motivated by the activity monitoring and finally the commonly used components of the activity recognition chain.

Chapter 3: describes the sensor technologies used in this thesis to collect the activity data, addresses the design of the data collection experiments and software tools used to collect and process the inertial sensor data.

Chapter 4: presents the overview of the design of the activity recognition system implemented in this thesis, including: preprocessing steps, signal segmentation, feature extraction & selection and classification schemes.

Chapter 5: presents the implementation and evaluation of the presented activity recognition algorithms on the daily living activities datasets.

Chapter 6: summarizes the thesis, concludes the research novel contribution and gives some ideas for future research directions.

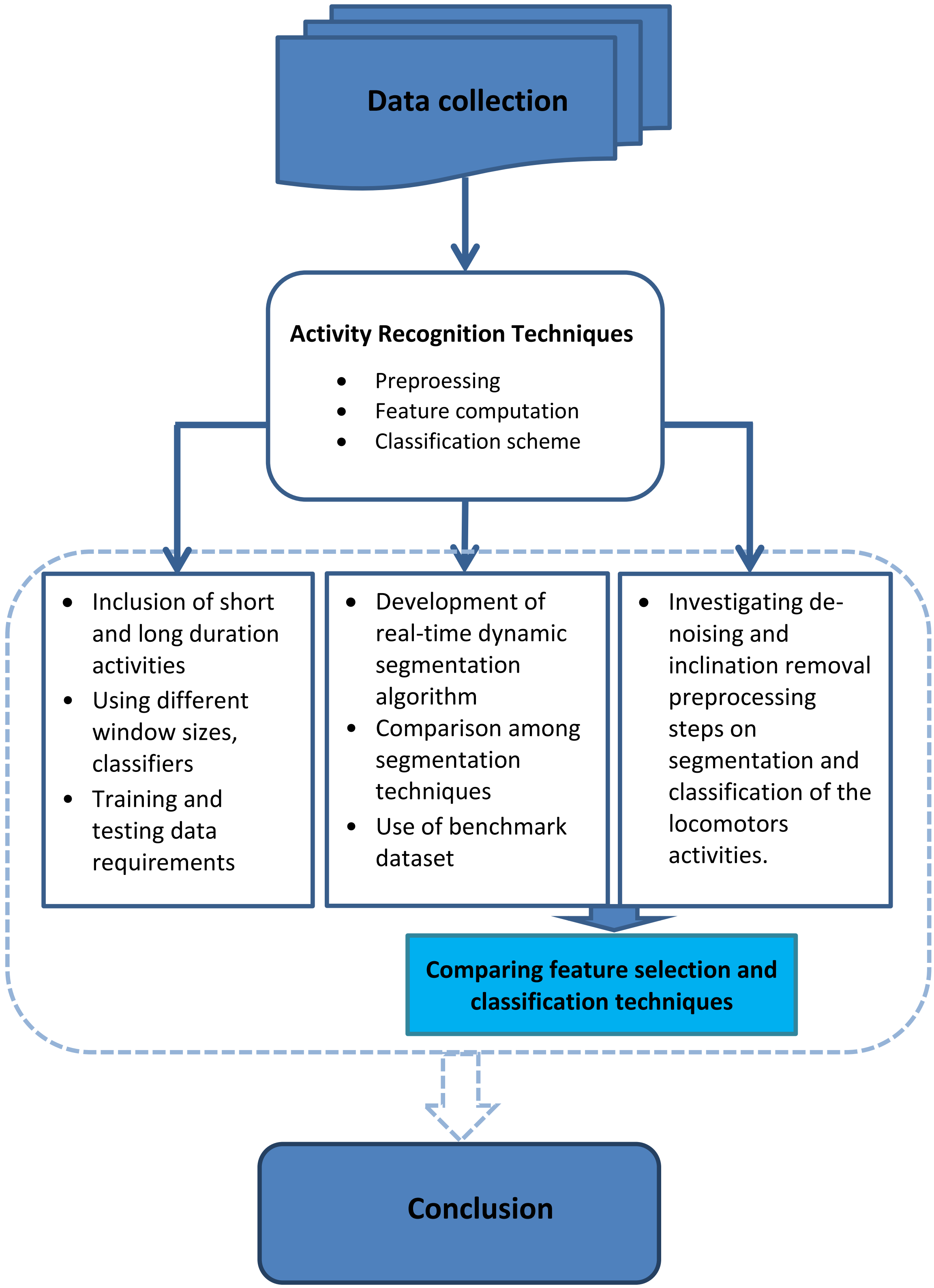

Figure 1-1 Dissertation schema

2

Literature

With recent advances in wearable sensing and ubiquitous and pervasive computing, tremendous research has been done for the application of this technology in a variety of fields, benefiting various everyday life applications. This chapter gives an overview of the research that has been carried out in the past regarding the use of this technology for activity monitoring applications. Section 2.1 describes the type of sensing approaches used in activity monitoring. An overview of the applications which have been motivated by the activity monitoring by using wearable sensors is outlined in section 2.2. Section 2.3 reviews commonly used components of the activity recognition chain and then finally a conclusion section narrates the considerations which are drawn from the literature studies.

2.1 Technologies for activity recognition

Different types of technologies and approaches have been used in the human activity recognition related problems. The selection of the sensing technology strongly depends on the type of the application, and possible choices include wearable sensors and home based video tracking. Several aspects need to be considered before choosing the sensing technology:

i. Cost of the system

ii. Privacy

iii. Comfort ability

iv. Maintenance

v. Usage

This section describes the approaches which have been commonly used in the activity recognition problems: video-based systems, environmental sensors-based systems, and wearable sensors.

2.1.1 Vision-based approach

This approach employs the installment of cameras inside the laboratory or home to recognize activity of daily living (ADL). While marker-based systems are very accurate in quantifying and describing movements, in home-based scenarios or uncontrolled indoor conditions, markerless systems may represent a viable alternative: in [35] video cameras are employed for marker less vision-based human motion analysis; a Microsoft Kinect depth camera is used in [8] to recognize the daily living activities of elderly people in a smart indoor environment; moreover, in [36], a Microsoft Kinect's depth camera is used as an ambient sensor for position and orientation tracking for an indoor monitoring system for Parkinson's disease (PD) patients.

Vision-based activity recognition techniques provide very detailed context information. However, these types of systems present some disadvantages: they have difficulty to trace the person in natural settings, where more than one person is present in the scene. Moreover, vision-based systems are not pervasive, as the monitoring of the activities is confined to the infrastructure where cameras are installed. Then, these systems face privacy concerns due to the video recording, as they are able to capture information coming also from un-cooperative people; in many cases, some people don’t want to be monitored by the cameras throughout the day. The last issue would be complexity, since video processing techniques are relatively computationally expensive, so this fact makes a real time activity recognition system to be less scalable.

2.1.2 Environmental sensors-based approach

In this approach, ADL are monitored through the interaction of the person with the home environment. Different sensors are installed inside the home and activities are usually monitored based on the condition of the object(s) with which a person interacts. Common examples of environmental sensing systems are the intelligent homes [37] [38] [9] [39] [40]. These systems can fairly recognize complex activities (e.g., sleeping, eating, washing dishes, vacuuming, taking a shower, preparing food, etc.), because they rely on data coming from the instrumented objects which people are supposed to interact with (e.g., stove, washing machine, vacuum, shower, etc.).

These sensors have fewer restrictions than video based sensors. Functionality of these types of systems is limited, as activities can’t be tracked if a person comes outside the deployed environment. Moreover, the installation and maintenance of the sensors usually require high costs. Plus, since the recognition of activity is basically indirect (as it is associated with the environment, and not with the subjects), in presence of more than one person, it may be difficult to associate an activity to one person.

2.1.3 Wearable sensors-based approach

Wearable sensors are the most commonly used sensors for the activity recognition. These sensors are placed over the body to recognize ADL with no restriction to the infrastructure. Wearable sensors can collect daily physical activity data patterns over a long period of time as they can worn as wearable devices, integrated into jewelry [41] [42] or clothing [43] [44].

Among the range of body-attached sensors, accelerometers, gyroscopes, foot switches, magnetometers and pedometers are most commonly used to capture and analyze ADL in free-living environment. Examples are sitting, standing, walking, cycling, running, and exercising.

Moreover, such sensors are low-cost, light weight, small in size and unlike video sensors they are not considered as a threat to people’s privacy. Inspire to these qualities, in this thesis, an inertial measurement unit (IMU) comprising a tri-axial accelerometer and a tri-axial gyroscope is used to recognize the daily living activities.

2.2 Use of wearable sensors for activity recognition

This section describes the different applications used in activity recognition related problems. In wearable technology, both accelerometers and gyroscopes have been used separately or together to analyze the movement. The location and number of sensors is usually dependent on the type of the activities and the problem to be studied. In [13] [19], multiple accelerometers are used to examine different daily living and household activities. Some of the studies found that placing a tri-axial accelerometer in proximity of the chest or waist is the best position to study whole body movements [26] [17] [5]. Accelerometers or gyroscopes attached to the lower limb are more often used to analyze gait patterns [21] [45] [46].

Therefore, the following subsections will give a list and short description of the different application areas.

2.2.1 Fall detection

Falls are a common problem in the elderly population: approximately 20-40 % of people aged 65 and over living at home fall each year. While about a half to two-thirds of the falls result in some type of injury, up to 10 % of these falls result in a fracture [47] [48] [49] [50]. Wearable inertial sensors are widely used for fall risk assessment and detection [51] [52]. Since it is considered that fall is often followed by a lying posture, thresholding on the signal magnitude vector (SVM) peaks is a common way to identify the falls [53]. In [54] a detailed survey on fall detection approaches is given.

2.2.2 Fitness and sports

In sport, accelerometers, gyroscopes or global positioning system [GPS] receivers are used to monitor the ongoing activities. These sensors are usually attached to the athlete's body or to the sports equipment to measure different physical quantities, such as acceleration, position and velocity.

Inertial sensor-based sports applications vary from aquatic to non-aquatic conditions. Ermes et al. [55] presented a method to recognize sports activities such as playing football, running, exercising with a rowing machine and cycling. Montoye et al. [56] and Parkka et al. [57] use inertial sensors to recognize the daily living and sports activities such as walking, treadmill walking/running, ergometer and calculate the energy expenditure. In aquatic sports, rowing and swimming strokes characteristics and performance are measured by [58] and [59].

2.2.3 Gait analysis

Accurate identification of the initial foot contact and terminal contact times are generally considered to be useful to capture the correlation between the normal gait and pathological gait [60]. In gait analysis, gyroscopes have been extensively used to calculate the initial contact (IC) and terminal contact (TC) times of the foot and their results are compared to either motion analysis systems and force plates [61] [62] [63], or foot switches [64] [65]. It has been found that gyroscopes can accurately detect gait events, if compared to reference systems, with negligible errors. Pappas et al. [66] use a shoe mounted gyroscope to calculate the four gait cycle phases: stance, heel-off, swing, and heel-strike. They validated their results against those obtained with motion capture. The GaitShoe system consisting of three uni-axial accelerometers, three uni-axial gyroscopes, two bi-directional bend sensors, two pressure sensors, four force sensors and electric field height sensors was used to detect the heel-strike and toe-off events [67].

2.2.4 Sit/stand transitions

The ability to perform sit-to-stand and stand-to-sit transitions are inversely associated with fall risk in elderly and PD patients [68]. The assessment of these transitions has thus significant importance in clinical studies. To this aim, a tri-axial accelerometer is used to recognize the different postural transitions including sit-to-stand and stand-to-sit transitions [18] [17]. Sit-to-stand and stand-to-sit transitions can be automatically identified as periods of activity [69], and they can be recognized by identifying the preceding and succeeding postures as sitting and standing [70] [71].

In clinical settings, Timed Up and Go (TUG) test is a very common test used to assess a person's mobility, and it requires both static and dynamic balance. In this test, both sit-to-stand and stand-to-sit postures are present [72].

2.2.5 Locomotion

Inertial sensors have also been used to identify and classify the different daily living and sports activities. In a variety of studies, multiple sensors have been used, with number ranging from 1 to 7 on different body locations. The most common locations are the thigh and the waist or chest [73] [70] [71] [74] [75].

The majority of the studies have investigated walking, stairs ascending, stairs descending and running activities as these are the most frequent occurring activities in daily life [17] [21] [12]. It is reported that accurate classification among walking and stairs walking activity is a challenging task, because these activities share very similar patterns of the lower limb movement among subjects [76]. Although existing systems have reported 13 excellent classification accuracy results, there is still room to allow accurate automatic identification and classification of these activities in real time scenarios.

2.3 Activity recognition system components

In activity recognition problem, different methods have been used to identify the physical activity from raw inertial sensor data. However, the common flow chart of the recognition system is divided into five main components: preprocessing, segmentation, feature extraction and selection, classification. This section elaborates on the most commonly used methods for each block. Figure 1 shows the work flow of the activity recognition system.

2.3.1 Pre-processing - De-noising

When dealing with a physical activity recognition problem, it has been argued that denoising inertial sensor data is necessary in order to be able both to extract the relevant information [27] [28] [29] [30] [17] and to identify the gait events from smooth signals [77] [31] [32] [33] [34] [78]. De-noising can be considered as the combination of the preprocessing steps that are performed to minimize the effect of noise (e.g., by filtering) and sensor misplacements (e.g., by considering a reference position for the sensor). For this second source of error, in previous works, it has been assumed that the correction of acceleration and angular velocity is necessary due to the inclination correction of the sensor and the effect of the gravity on the signal [34] [79].

2.3.2 Segmentation

On-body sensors are collecting and continuously outputting streams of data and one important task is to divide this incoming data stream into segments, in order to be able to associate, to each segment, some relevant information associated with the activity that is monitored within that segment. In the past, various methods have been applied to divide the signal into segments, the most common ones among them being the use of fixed window length and the application of event-based windows.

2.3.2.1 Window-based segmentation

In this technique, the data stream is divided into consecutive windows of fixed length. In the case of physical activity recognition, different window lengths have been used in the past studies: 1s [53] [11], 2s [80] [22], 3s [17], 4s [15], 5s [81], 6.7s [13] 10s [12] [5] [26] up to 30s [82]. Time windows can be overlapping [82] [13] [83] [81], or disjoint [84]. One limitation of this approach is that problems can arise if an activity lasts for shorter or longer time periods than the pre-defined window length.

2.3.2.2 Event-based segmentation

In terms of gait event detection, a gyroscope placed at the shank has been proven to be acceptably accurate in healthy gait walking up and down an incline [77] and in pathological [63] [62] and in healthy gait when walking on level ground [63] [64]. Gyroscope placed on the foot and on the shank has been used for locomotion pattern classification, including descending and ascending stairs [31] [85] [32], and it was concluded that it is possible to detect gait events from the locomotion activities performed by the subjects. With an event-based segmentation, foot-off or foot strike events are used to dynamically define the length of the successive windows: the size of the windows thus depends on the type and duration of the activity.

A number of different approaches have been proposed for identifying either foot strike or foot-off (or possibly both events) from body-worn sensor signals. Chen et al. extracted all peaks (mid-swing) from the accelerometer anterior-posterior component, and used the center of two consecutive peaks to identify the flat-foot event within a search window that is a part of the estimated gait cycle [31]. In [86], each foot-off event was detected based on the local minimum search from the expected foot-off point to zero-crossing of the next swing phase.

2.3.3 Features extraction

Extracting useful information from the raw segmented data facilitates to construct an effective and efficient activity recognition system, both computationally and performance-wise. In general, standard classification algorithms are not directly applied to raw time-series data. Instead, we first transform the raw time series data into useful information [87]. To accomplish this different time domain, frequency domain and heuristic features have been calculated from the segmented data in the activity recognition problems.

2.3.3.1 Time domain features

Time-domain features are simple statistical measures which are derived from the segmented data. Most commonly used time-domain features in activity monitoring are the variance, median, kurtosis, mean, skewness [88] [20], standard deviation [12] and interquartile range [76].

2.3.3.2 Frequency domain features

Frequency-domain features are the coefficients derived from the coefficients of the Fourier transform, normally using the fast Fourier transform (FFT). These coefficients represent the amplitudes of the frequency components of the signal thus giving information on the frequency distribution of the signal energy. Different methods can then be used to characterize the spectral distribution from these coefficients.

For example, a subset of the different FFT coefficients can be used [22] [25]. Alternatively, information from a number of coefficients can be combined to give a single feature. Examples include spectral energy, which is the sum of the squared FFT coefficients within a specific frequency range [89] [11] and the frequency-domain entropy, which is the normalized information entropy of the FFT components [13].

2.3.3.3Other features

Different methods have been used to derive certain heuristic features to quantify the amplitude of the data. Before these features are derived, a high pass filter is applied to the signal to remove any baseline offset. These features include the signal magnitude area [69], peak-to-peak acceleration [90], mean rectified value [91] and root mean square [73]. This type of feature is often used to differentiate between static and dynamic activity [69].

2.3.4 Features selection and dimensionality reduction

Each individual has its own way of carrying out movement, which results in the variety of different patterns under the same movement type. Even the variation in the same movement may occur in an individual over a long period of time. Thus, this behavior leads to variability in the features calculated from body-worn sensor data [92]. Hence, it is a need to identify the robust features set which can effectively differentiate among different activities, but should show little variation among the different subjects and the same movements [93]. Moreover, it is important to minimize the redundant features as this can reduce accuracy with some classification methods and unnecessarily increase the computational cost [94].

A number of different feature selection techniques have been used to identify the useful features for activity classification. These methods are generally divided in to three groups, wrapper methods, filter methods and embedded methods. Zheng et al [95] compare the performance of one filter method: Relief-F and two wrapper methods: Wrapper Method based on Single Feature Classification (SFC) and Wrapper Method based on Sequential Forward Feature Selection (SFFS) on the classification of the physical activity. In [84] dimensionality reduction method: Principle component analysis (PCA) method and wrapper methods:

Sequential Backward Feature Selection (SBFS) and SFFS method has been used to compare their performance on the activity recognition. Both studies come up with the better performance of the SFFS method.

2.3.5 Learning

In ADL recognition systems, the appropriate feature vector which has been calculated from a segmented sensor data is forwarded to a classification algorithm. These techniques usually fall under the *Machine Learning* term, where classification algorithm interprets, analyzes and associates each feature vector to one activity class. Learning methods are usually divided in to three classes: supervised, unsupervised and semi-supervised. In supervised learning, target class (e.g. walking, standing, running) against the feature vector is provided to the classifier, so that the algorithm is correctly trained and associates the feature vector to the corresponding class. While in unsupervised learning, the algorithm assigns the feature vector to a cluster based on some similarity criteria among them, without having the prior knowledge of the target class of the feature vector. The clusters assigned by the algorithm represent the activity classes e.g. walking, standing, running. Semi supervised methods combine a usually small amount of labeled data with large amounts of unlabeled data to train the classifier.

Supervised learning methods have been commonly used in the literature of activity recognition problems. As of now, no agreed method is universally considered as performing best in this context, since their behavior and performance vary depending on the type of activities to be monitored. Commonly used supervised classification methods in the field of human activity monitoring are the following:

- Decision tree is commonly used in classification problems using the concept of information gain or Gini gain [96]. Various decision tree classifiers including C4.5 [13] [81], J48 [12] [97] [89] and decision table [97] [13] and best first tree [24] have been used in activity monitoring.
- K-nearest Neighbours (kNN) is an instance-based learning algorithm which classifies the instances by comparing them with pre-learned training samples [97] [89] [22] [24].

- Nave Bayes is a supervised approach that uses probabilistic knowledge to assign the test sample to a class [97] [16] [81].
- Support Vector Machines (SVM) is based on the statistical learning theory introduced by Vapnik in the early 1990s [98]. [99] [16] [85] [81].
- Artificial neural networks (ANN) including Multi-Layer Perceptron neural networks [100] [21] [24] [11].
- Markov models, including hidden Markov models (HMM) [101] [102] [103].
- Threshold based classifiers [53]

Unsupervised learning approaches are by far less commonly used for activity monitoring. These methods construct models directly from unlabeled data, using e.g. density estimation or clustering. Examples of unsupervised learning of different activities are presented e.g. in [104] [105]. Finally, some of the studies find promising results with semi supervised learning methods applied for human activity monitoring. Semi supervised approaches for activity recognition are used in [106] [107] [108] [109].

2.4 Conclusion

In this chapter a general overview of recent approaches related to physical activity recognition has been presented. A wide range of technologies, methods and solutions have been highlighted for the different components of activity recognition systems. Four major topics have been discussed in this chapter, the type of sensing approaches, activity recognition systems inspired applications, and finally different machine learning methodologies. The rest of this thesis will only focus on a fraction of the here presented approaches, which is specified in this section.

The goal of the study is to check the physical active status of an individual in daily routine. So over the wide range of activities recognized in the previous studies, this thesis focuses on the most common daily living activities with significant energy expenditure, thus focusing on locomotion: walking, sitting, standing, running etc. These activities are associated with the wellbeing of a person and could be helpful to find the health status. A complete list of the activities used in this work is based on the study being carried out and is described in section 3.3.

From the above-mentioned sensing technologies, an inertial sensor including accelerometer and gyroscope has been used to identify and classify the daily living activities. Therefore, as suggested by various related works, the combination of them will be beneficial for recognizing the physical activities.

Considering machine learning methods, Chapter 3 will present a complete data processing chain for physical activity recognition. This includes the evaluation of preprocessing, segmentation techniques, feature extraction and selection and learning methods for activity recognition.

Finally, as discussed in Section 1.1, the main motivation for developing different methods in this thesis is to be used in healthcare applications. With the precise monitoring of physical activities, the here presented solutions can tell how strictly individuals follow general or custom recommendations given by physicians and regarding daily mobility. Moreover, the proposed approaches can also be directly used in general fitness applications, where detailed information about the intensity, quality, and duration of the performed physical activities is of interest for the user.

3

Recording tools, experimental design, datasets

This section describes the sensor technologies used to collect the activity data, and illustrates the design of the experiments performed in the different studies. A brief description of the software tools used to collect and process the inertial sensor data is also discussed in the respective sections of this chapter. Finally, the datasets used in the different studies will be described.

3.1 MEMS-Inertial measurement unit (IMU)

The acronym MEMS (Micro-Electro-Mechanical Systems) refers to microscopic devices with sizes between 1 micron and 1 mm. This technology enables to combine, in a single silicon chip, electrical and electronic components with mechanical elements, optical, or fluidic. The inertial sensors are composed of mechanical and electronic elements and measure acceleration and angular velocity with respect to one or more axes in a reference three-dimensional space.

3.1.1 Accelerometers

The most widespread MEMS accelerometers fall into two categories: piezoresistive and capacitive [110].

Capacitive accelerometer

Figure 3-1 shows the principle of operation of a very simple capacitive accelerometer. The device can be schematized as a second order mechanical system, composed by a mass, a spring and a damper.

When the external acceleration is acting on the system, the mass moves relative to the system in the opposite direction, and the displacement is then detected by a capacitive system. This is formed by a series of electrodes connected to the mass, which are free to move, and others are fixed to the substrate. The displacement of the mass causes a change in the capacitance which is measured by the electrostatic system. So by the direct measurement of this change it is possible to calculate the value of external acceleration.

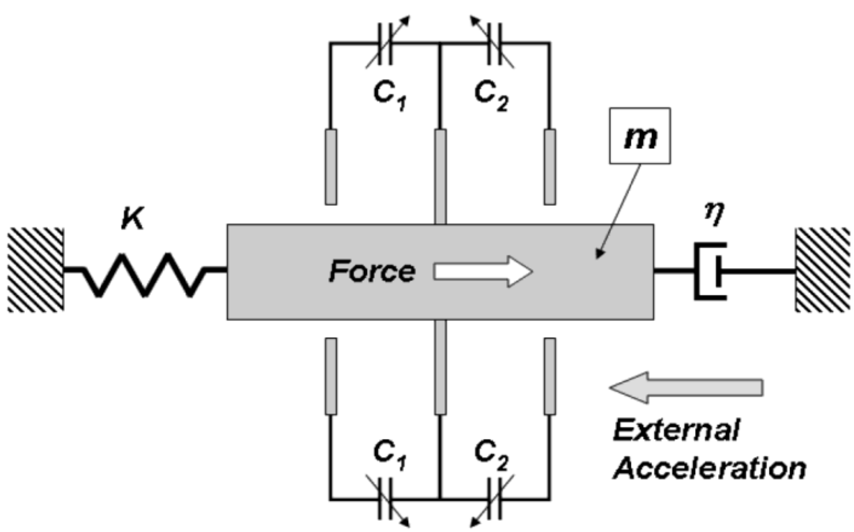

Figure 3-1 Schematic of Capacitive accelerometer

Piezoresistive accelerometer

The mechanism of a piezoresistive accelerometer is very similar to the one of a piezoresistive pressure sensor. Some piezoresistors (shown as black dashes in figure 3-2) are located on the upper surface of the device and electrically connected so as to form a Wheatstone bridge.

When an acceleration acts on the system, the proof mass reacts by moving and then deforming the thin foil placed over it to which it is connected. This deformation causes the change in resistance of the piezoresistors. The electronic circuit detects the resistance change and calculates the amplitude and direction of acceleration of the electric signal.

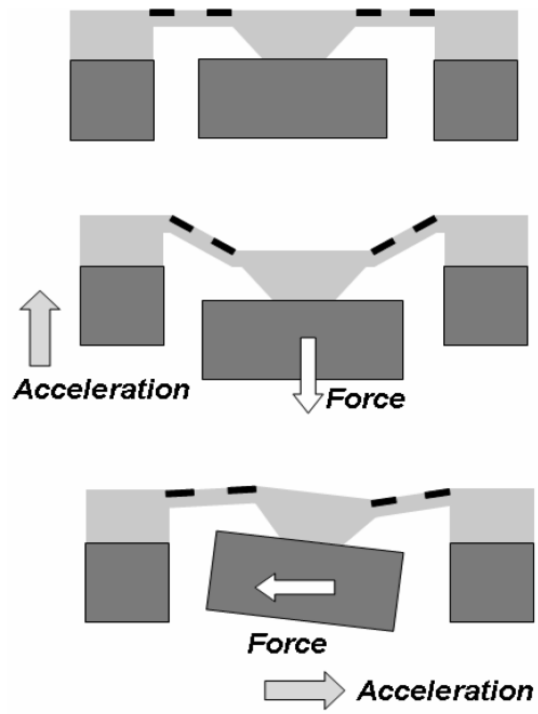

Figure 3-2 Schematic of piezoresistive accelerometer

3.1.2 Gyroscope

Most MEMS gyroscopes are based on energy transfer between two vibratory modes of a structure, caused by the acceleration of Coriolis. The Coriolis acceleration is the result of Newton's laws applied in a rotating frame. The gyroscope converts the angular velocity input in a shift of its mass test, using the Coriolis acceleration [111]. In Figure 3-3 shows the principle of a simple gyro scheme.

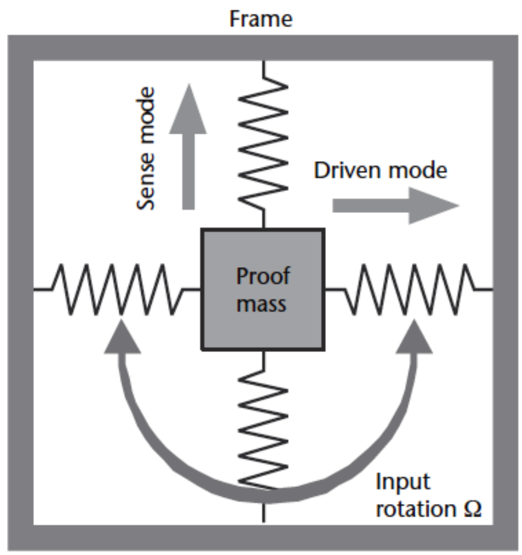

Figure 3-3 Schematic of MEMS gyroscope

The gyroscopes, therefore, are based on a mechanical flow into resonance structure (Driven mode) that excites secondary oscillation (Sense mode), via the Coriolis acceleration, caused by the rotation. The amplitude of this secondary oscillation is directly proportional to the angular signal to be measured.

An obstacle to this technology is the small amplitude of the Coriolis force (Force Sense) than that which is applied in the orthogonal direction (Driven Force). One way to counter this problem is to use structures with a high output/input ratio, such as for example vibrating structures in resonance, the Sense mode.

The continuous and rapid technological development has allowed us to produce high-performance MEMS inertial sensors and reliable [112] allowing its use in different areas of technology at a relatively low cost. The use of these sensors is widely spread and can be found in the field of automobiles (for example, used as support to the GPS survey, in airbag systems, in control systems for safety belts, of the active suspensions and more) or in the field consumer electronics (image stabilizers, tilt-sensor, free-fall detection). In the medical field you will have applications in the control of assistive devices [66] [113], activity monitoring [114] and measures of posture and movement [115] [116].

In this work an inertial sensor consisting of a tri-axial accelerometer and tri-axial gyroscope is used to construct the activity datasets.

3.2 Device – BiolabIMU

BiolabIMU is a self-built-in wireless device consisting of a tri-axial accelerometer and a tri-axial gyroscope interfaced with Bluetooth, and equipped with a microcontroller, shown in figure 3-4. An ADXL345 tri-axial accelerometer measures acceleration in a selectable range of ± 4 g with a fixed resolution of 10 bits (Analog Devices Inc., 2011). The ITG3200 gyroscope is composed of three independent gyros, which measure the angular velocity around the X axis (roll), y (pitch), and Z (yaw) (InvenSense Inc., 2010). It provides a digital output in a range of ± 2,000 deg / s with a resolution of 16 bits. The sensitivity is 14,375 LSB for deg / s. The WT - 12 is a Bluetooth + EDR (Enhanced Data Rate) class 2 with data transfer speeds up to 2.3 Mbps and firmware iWRAP (Bluegiga, 2009). It has an integrated antenna and operates in the ISM band (Industrial Scientific and Medical) at 2.4 GHz, which allows communicating with the remote computer. The ATMEGA328 microcontroller is a C - MOS 8 bit ultra-low power based on the AVR RISC architecture produced by Atmel (Atmel Corporation, 2011). This unit has been used in most of the studies described in this thesis.

Figure 3-4 Biolab IMU front and back view

3.3 Data collection

Three different datasets were collected over different daily living activities. A brief description of each dataset is given below, together with the experimental design associated with the dataset.

3.3.1 BioLab[1] dataset

3.3.1.1 Device

Experiments were performed by using a BiolabIMU attached to the waist of the subjects with axes along anterior posterior, vertical and medio-lateral directions. Data were transmitted to the system through Bluetooth connection with a sampling rate of 100 samples/s (range of the sensor ± 4g).

3.3.1.2 Participants

Nine younger adults (5 females and 4 males, ages 22 to 34 years, height 171.4 ± 6.7, weight 68.37 ± 14.4) were recruited for the experimentation. All subjects were healthy without any pathological disorder. Each subject was pre-informed about the activities and path by giving a written note.

3.3.1.3 Protocol

Subjects were asked to follow a path of different physical activities at their own selected speed. The whole path was organized inside a building: the circuit involved standing (with random durations in the range 2–6 s), stand-sit, sitting (2–6s), walking (approximately 115 m path, with three 90° different turns), stair descending (48 steps, with landing on 12th, 24th and 36th step), brief walking (4 or 5 steps), standing (2–6s), stand-sit, sitting (2–6s), stair ascending (same flights of stairs) and then walking. Sitting activity was performed on two different seat heights (44cm and 36cm). Each time, transitions between sit and stand were performed 4 times, and the time taken by the participant during sitting and standing varied between 2 to 6 s, to check the ability to identify activities lasting for few seconds.

3.3.2 BioLab[2] dataset

3.3.2.1 Device

Experiments were performed by using a BiolabIMU fixed on the shank (lateral position) of the dominant leg. The accelerometer x-axis was positioned in the anterior-posterior direction, the y-axis in the inferior-superior direction and the z-axis in the lateral-medial direction. The gyroscope rotations were defined as follows: x-axis (coronal plane); y-axis (transverse plane); z-axis (sagittal plane).

3.3.2.2 Participants

Nine healthy adults (5 females and 4 males, ages 29 ± 5 years, height 171.4 ± 6.7, weight 68.37 ± 14.4) were recruited for the experimentations.

3.3.2.3 Protocol

Experiments were carried out in the university building, except running, which was performed outside the campus building. All participants were asked to carry out activities at their self-selected speed and had to walk on a predefined route. During the first 5 s of the experiment, the subjects stood still in an upright position to initialize the offset; then, they followed a route, including a walking path of 50 m, opening and closing a door, stairs ascent (SA, staircase of 46 steps), a few walking steps, opening and closing a door, running (outside the building along the path of about 150 m), opening and closing a door, stairs descent (SD), opening and closing a door, and walking. At the end/start of each activity, subjects stood still for few seconds in order to label the data correctly. Data were collected at a sampling rate of 100 Hz. Labeling was done by visual inspection by one experimenter.

3.3.3 BioLab[3] dataset

In this dataset, data were recorded from seven healthy adults with the same sensor settings as mentioned above. Subjects participated in this dataset were different from other datasets. Three physical activities were performed by the participants; walking, stairs ascending and stairs descending. In this dataset, thus, no running activity was performed and is used in the studies as validation data along BioLab^{2}dataset.

3.4 Software tools

In this study two software tools; Matlab and Weka are used for signal processing and classification of daily living activities.

3.4.1 Kinematic Data Viewer App

A java based Kinematic Data Viewer App was developed to streaming data from inertial sensor to laptop (See Appendix B for further details).

3.4.2 MATLAB

Matlab is a high-level language for scientific and engineering computing, used for curve fitting, data classification, signal analysis, and many other domain-specific tasks. It provides a graphical interface for visualizing data and tools for creating custom plots. In this study, signal preprocessing, segmentation and feature computation are performed by using Matlab environment.

3.4.3 WEKA

Weka (Waikato Environment for Knowledge Analysis) is a free machine learning software written in Java. It provides a tool to implement a large number of data mining algorithms and a user friendly graphical interface to manipulate and visualize the output results. A great description of the Weka toolkit can be found in [117], includes the machine learning concepts the toolkit uses, and practical guide for using the different tools and algorithms. In this study for the training and evaluation of all classifiers, the Weka toolkit is used [118].

4

Activity recognition approach

This section introduces the overview of the design of the activity recognition system implemented in this thesis. A brief description of the methodologies used to evaluate the activity data is discussed in the respective sections of this chapter.

4.1 Overview of the approach

The proposed approach examined in this study is to automatically recognize human activities using a single inertial sensor, and it is composed of some main steps: a systemic analysis was performed on the collected datasets which facilitates to implement those parameters which makes the system light weight, implementable in the real time and meanwhile maintains the accuracy of the activity recognition; this means the consideration of de-noising steps, implementation of possible low computational segmentation approaches, and then feature set and the classification. A benchmark dataset PAMAP2 is also used to validate the proposed approach.

4.2 Activity recognition approach components

Activity recognition process from sensor data can be divided into four main steps: 1) signal preprocessing, 2) segmentation, 3) feature extraction and selection and 4) classification.

4.2.1 Preprocessing

Signal preprocessing usually includes the band-pass filtering of the signal to remove the undesirable noise from the signal. The work presented here focuses on the effect of the most common pre-processing steps used when gathering inertial sensor data for activity recognition, i.e., inclination correction and filtering.

4.2.1.1Inclination Correction

Due to the nature of the monitored physical activities, the sensor attached to the body is prone to move with respect to the body segment, thus producing an unintended bias in data recording. To minimize the influence of sensor inclination, each data channel value was removed from the average value obtained when standing still for 5 s before starting the activity path. Further detail is given in section 5.4.

4.2.1.2Signal Filtering

To remove the noise from the signal, an online filter was also implemented to smooth the current sample by applying the following Equation (4.1):

$$y_n = b_0 x_n + b_1 x_{n-1} + \cdots + b_M x_{n-M} - a_1 y_{n-1} - \cdots - a_N y_{n-N}$$

$$= \sum_{k=0}^{M} b_k x_{n-k} - \sum_{k=1}^{N} a_k y_{n-k} \tag{4.1}$$

where y is the filtered output of the input x, and b and a are the coefficients of the first order low pass filter that were computed by considering a cut-off frequency of 10 Hz, as a cut-off frequency of 10 Hz is motivated by previous works [31] [85]. We have applied different orders of low-pass filtering (i.e., choosing different values for N and M) and chose N = M = 2, as this configuration offers pretty low complexity for the implementation, still giving fair values in terms of selectivity (−15 dB at twice the corner frequency, set at 10 Hz). Further detail is given in section 5.2.

4.2.2 Segmentation

Two segmentation techniques have been used in this work: static segmentation and dynamic segmentation.

4.2.2.1 Fixed length window segmentation (Static)

The length of the window introduces a real-time recognition delay equivalent to the duration of the window. The longer the window duration is, the longer the real-time recognition delay will be. In this study, data were segmented using sliding windows of different size (0.5 s, 1 s, 1.5 s, 2 s, 2.5 s and 3 s) to find out their effect on the daily living activity classification. Windowed data were labeled based on the ground truth knowledge of the activities: when dealing with more than one activity within a window, this was labeled by considering the activity that was more present within that window. Use of static segmentation technique can be found in section 5.1 and 5.3.

4.2.2.2 Event-based segmentation (Dynamic)

In dynamic segmentation, gait events were identified from the locomotion activities data to segment the signal into a gait cycle. Angular velocity in the sagittal plane g_z was used for the gait cycle detection, based on the identification of the foot-off events. To achieve this task, local minima and maxima were updated and the foot-off event was identified when specific conditions were met, as it will be shown in the following.

The algorithm starts to find two successive zero-crossings (a negative zero-cross followed by a positive zero-cross), that are hypothesized as characteristic of the swing phase: the swing phase is thus segmented if the maximum value of the angular velocity in that direction is greater than 1.8 rad/s; under this circumstance, its location is hypothesized as the mid-swing position. Once the swing phase is identified, the algorithm starts searching for the following minimum value, as it corresponds to the foot strike event. Once the foot strike event is found (and located at t_{fs}), the algorithm searches for the local maximum t_{MAX} and local minimum t_{min}, and then verifies the following condition:

$$t_{min} - t_{MAX} \geq 60\ ms\ \&\&\ \ g_z(t_{min}) \leq 1.4\ rad/s\ \&\&\ \ t_{MAX} - t_{fs} \geq 70\ ms$$

If the equation is satisfied, t_{min} is saved as the estimated location of the foot-off event. If this condition is not satisfied within 1.3 s (as it may happen in the case of transitions, or when the person is resting), then the algorithm discards the current saved swing phase and starts the search for the next swing phase. Each activity cycle – which represents one segmented window over which the features will be extracted – is thus defined by using two consecutive foot-off events. Dynamic segmentation methodology is outlined in Figure 4-1 and is adopted in section 5.2.

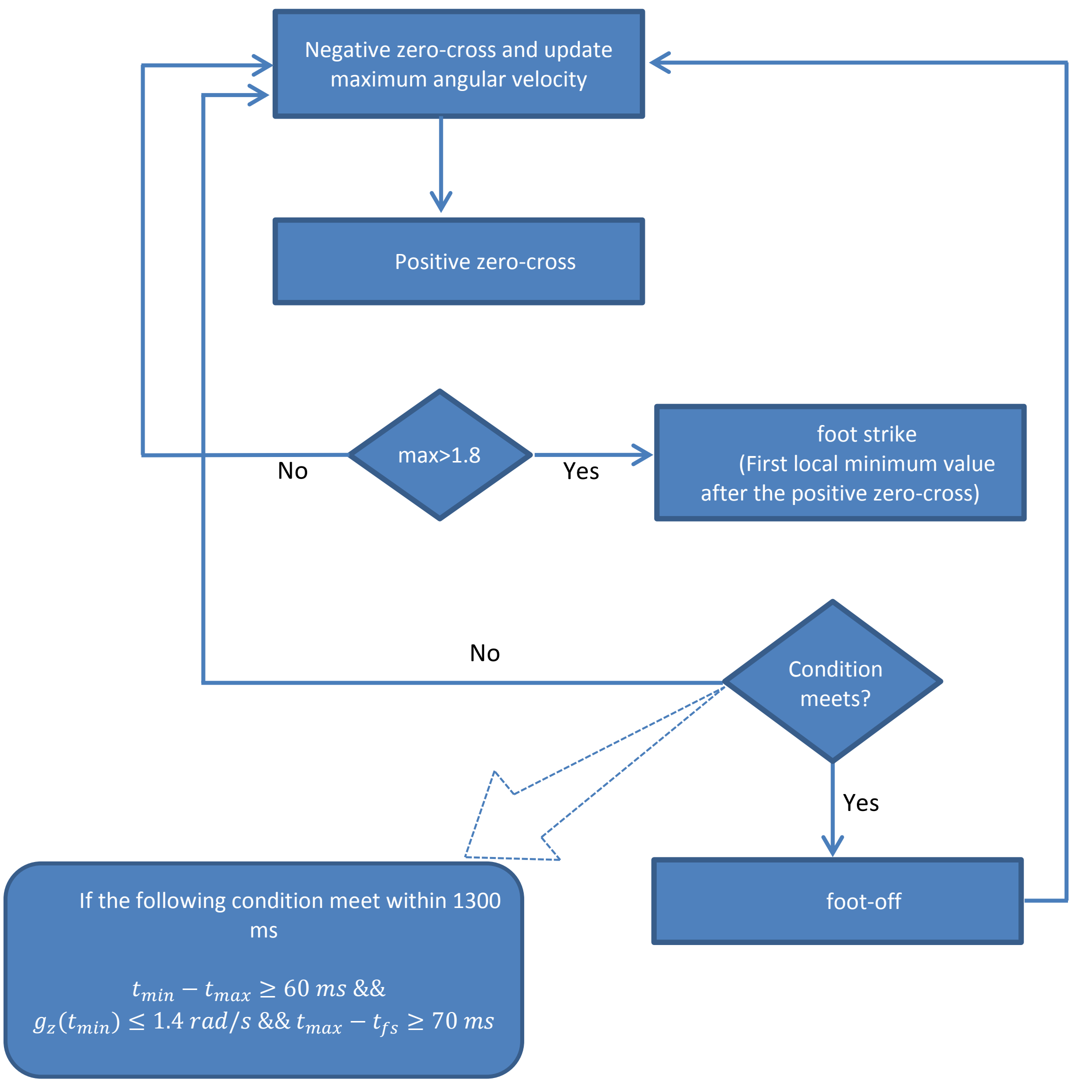

Figure 4-1 Event-based segmentation algorithm work flow.

4.2.3 Feature computation

4.2.3.1 Feature extraction

For each segment, a set of features must be extracted to identify the activity. In this study, different time and frequency domain features that are used in the literature for the activity recognition problem were derived from each axis and magnitude of the inertial sensor signal [25] [29].

Signal magnitude is considered as orientation independent and is useful in solving the sensor orientation inconsistency problem, and it is calculated as

$$a_{mag} = \sqrt{a_x^2 + a_y^2 + a_z^2}\,, \qquad g_{mag} = \sqrt{g_x^2 + g_y^2 + g_z^2}$$

where a_{mag} is the magnitude of the acceleration signals and g_{mag} is the magnitude of the gyroscope signals. Table 4-1 shows the list of features used in this study.

Table 4-1 Features description

No.	Features
1	Mean value along each axis (x, y and z) and magnitude
2	Median value along each axis (x, y and z) and magnitude
3	Skewness value along each axis (x, y and z) and magnitude
4	Kurtosis value along each axis (x, y and z) and magnitude
5	Standard deviation value along each axis (x, y and z) and magnitude
7	Correlation between axes (x_y, x_z, y_z, x_mag, y_mag, z_mag)
8	Energy value along each axis (x, y and z) and magnitude
9	1st five FFT coefficients

Time domain features

Time domain features which are derived in this study are mean, median, skewness, kurtosis, standard deviation and correlation-coefficients.

Mean and median: Mean is the average value of the signal over the segment. It is useful to differentiate among static and dynamic activities. Mean is calculated as

$$m_x = \frac{\sum_{i=1}^{n} x_i}{n}$$

Median for even and odd n is calculated as

$$median_x = x_{\left\lceil \frac{n}{2} \right\rceil}$$

$$median_x = \frac{\left(x_{\left\lceil \frac{n}{2} \right\rceil} + x_{\left\lceil \frac{n+2}{2} \right\rceil} \right)}{2}$$

Standard deviation: Standard deviation has been extensively used in activity recognition studies and is calculated as

$$std_x = \sqrt{\frac{\sum_{i=1}^{n} (x_i - m_x)^2}{n}}$$

Skewness: Skewness is calculated as:

$$Skewness_x = \frac{\sum_{i=1}^{n} (x_i - m_x)^3}{n\sigma^3}$$

where σ is the standard deviation.

Kurtosis: Kurtosis is calculated as:

$$Kurtosis_x = \frac{\sum_{i=1}^{n} (x_i - m_x)^4}{n\sigma^4}$$

Correlation: Correlation has been considered to improve activity recognition, when activities involve movement of multiple body parts [88]. It is also considered helpful for differentiating among activities that involve translation in just one dimension [81]. For instance, with correlation between axes it is possible to differentiate walking and jogging activity from stairs ascending and descending. Correlation is the ratio between the covariance and the product of the standard deviation between each pair of axes, as shown in the equation below:

$$Corr_{(x,y)} = \frac{cov_{(x,y)}}{\sigma_x \sigma_y}$$

where $cov_{(x,y)}$ is the ratio of covariance between the x and y axis of acceleration and $\sigma_x \sigma_y$ is the product of the standard deviations.

Frequency domain features

To obtain the frequency domain features, signal was first transformed into frequency domain, using a Fast Fourier Transform (FFT). To extract useful information from FFT signal, following features are used.

Energy: The periodicity in the data is reflected in the frequency domain. To capture data periodicity, the energy feature was calculated. Energy is the sum of the squared discrete FFT component magnitudes of the signal. The sum was divided by the window length for normalization. If x_1, x_2 , ... are the FFT components of the window then;

$$Energy = \frac{\sum_{i=1}^{|w|} | x_i|^2}{|w|}$$

where x_i are the FFT components of the window for the *x* axis and *w* is the length of the window.

FFT coefficients: The first five FFT coefficients (as calculated over each segment) were used, as these contain the main frequency components (up to 5 Hz).

4.2.4 Feature selection

Linear forward feature selection (LFFS) and SVM based feature selection techniques are used to obtain the most appropriate features to reduce the complexity and computational of algorithm.

These techniques are discussed in sections 5.2 and 5.3.

4.2.5 Classification

We tested the recognition performance of the five different classifiers; Naïve bayes (NB), k-nearest neighbor (k-NN), Decision tree (DT), artificial neural networks (ANN) and support vector machine (SVM) classifier on the selected features. Some studies pointed out the positive performance of these classifiers in the activity recognition problem [16] [13] [22] [11] [21] [119].

4.2.5.1 k-Nearest neighborhood

Instance-based classifiers such as the k-NN classifier, classification of unknown instances can be done by relating the unknown object to the known according to some distance/similarity function. Those instances which are less apart from each other by applying some appropriate distance function have more chances to put in a similar class as compared to those having more distance (Figure 4-2).

k-NN is a “lazy” algorithm; it does not use the training data objects to do any generalization. In other words, the training phase in k-NN is too short or quick that it is considered to be no real training in k-NN. So this type of classifier has less work to do at start but when actual classification is performed then these classifiers become more expensive.

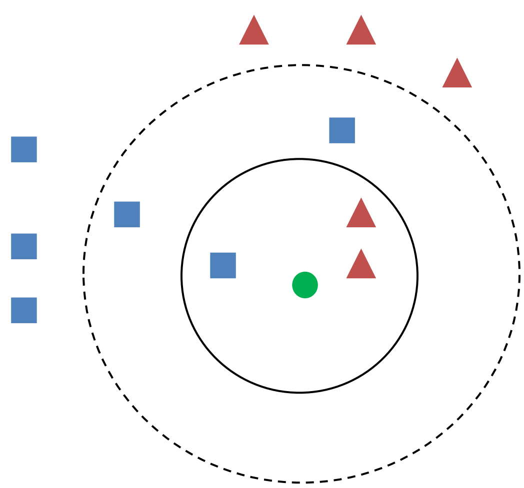

Figure 4-2 K-nearest neighborhood

Parameters selection: In the k-NN algorithm, one problem is the best choice of K number of nearest neighbors. In this study, 5 nearest neighbors have been chosen.

In the k-NN classifier, different distance metrics are used to classify between a test sample and the specified training samples. Euclidean distance is used in this study. Let x_i be an input sample with *k* features ($x_{i1}, x_{i2}, \ldots., x_{ik}$), *n* is the total number of input vector (*i*=1,2,…,*n*) and *k* the total number of features (*j*=1,2,…,*k*) . The Euclidean distance between two samples is defined as

$$d(x_i, x_l)=\sqrt{(x_{i1}-x_{l1})^2+(x_{i2}-x_{l2})^2+\cdots+(x_{ik}-x_{lk})^2}$$

4.2.5.2 Support vector machine

This approach of classification is considered as a good candidate due to its high generalization performance as it does not require any addition of prior knowledge, even when the input dimension is very high. It is a kernel based classifier which was initially developed for linear separation to classify the data in to two classes only.

The main idea behind this technique is that it maps the input features vector into a high-dimensional space to construct a maximal separating hyper-plane as the decision-making surface. Utilizing this decision boundary, the algorithm decides whether a new instance falls into one class or the other. Figure 4.2 shows the simple linear support vector machine. Major task of SVM is to maximize the margins between two classes of the hyper plane [120].

Linear classifiers using support vector machines: In linear classification, SVM divides the data among two classes by constructing a straight line hyperplane (Figure 4-3). Consider a set ‘a’ of training samples $(\mathrm{x_i}, \mathrm{y_i}) 1 \leq \mathrm{i} \leq \mathrm{N}\ \ \mathrm{x_i} \in \mathrm{R^d}$, where $\mathrm{y_i} \in \{-1,1\}$ is the class label to which xi belongs. Generalized form of linear classification function is $g(x) = w.x + b$, which draws a separating hyper plane $w.x + b = 0$. To satisfy $|g(\mathrm{x})| \geq 1|$ for all x_i, to maximize the distance between the hyperplane and the closest point we have to normalize *g(x)*.

Among the separating hyperplanes, optimal separating hyperplanes (OSH) is the one for which the distance to the closest point is maximal [121]. Since the distance to the closest point is l/ ||w||, to find the OSH amounts to minimizing ||w|| then the objective function will be:

$$min\, \emptyset(w) = {}^{1}\!/_{2}\ \| w \|^{2} = {}^{1}\!/_{2}\,(w.w)$$

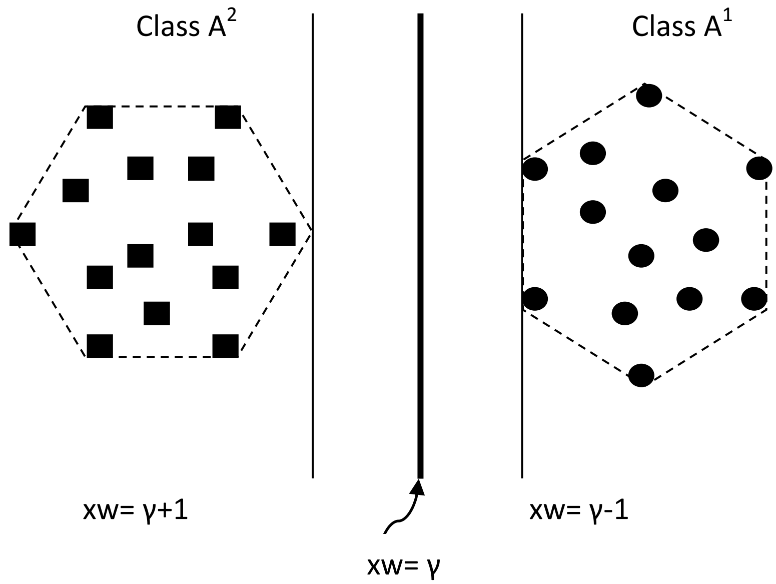

Figure 4-3 Linear support vector machine

Nonlinear classifiers using support vector machines: In nonlinear problem where data is not separated by a straight line, a penalty factor and slack variables are encountered and the objective function would be modified to

$$\emptyset(\mathrm{w},) = \frac{1}{2}(\mathrm{w.w}) + \mathrm{C}\left(\sum_{1}^{\mathrm{N}} \xi\iota\right)$$

On the other hand, in nonlinear problem the input data can be mapped to high dimension feature space by applying nonlinear function, so that the resultant feature space can be easily separated by constructing hyper plane (Figure 4-4). As a result dot product in the linear kernel is represented as

$$\mathrm{k(x,y)} := \big(\emptyset(\mathrm{x}).\emptyset(\mathrm{y})\big)$$

Equation below shows the final classification function for nonlinear problem.

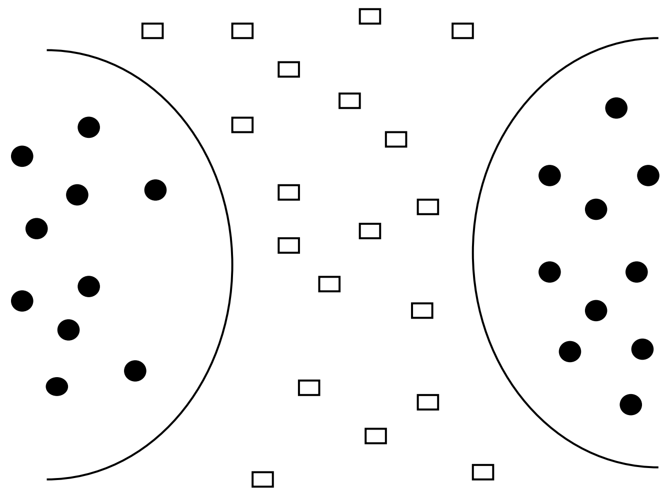

Figure 4-4 Non-linear support vector machine

Inner dot product $\left(\emptyset(\mathrm{x}).\emptyset(\mathrm{y})\right)$ defined the kernel function $\mathrm{k}(\mathrm{x},\mathrm{y})$.

SVM parameters: In the present study, the multi-class problem was solved by using pairwise classification (1-vs-1) [122]. Different kernel methods with varying complexity parameters were tested, and a polynomial kernel with complexity value of 1 performed best on the problem. The Kernel function used in this study is:

Polynomial kernel function $\quad \mathrm{K}\left(\mathrm{x_i},\mathrm{x_j}\right) = \left(1 + \mathrm{x_i^T},\mathrm{x_j}\right)^{\mathrm{p}}$

4.2.5.3 Naive bayes classifier

Bayesian classifiers (Naïve Bayes, NB) are statistical classifiers that calculate the probability of a given sample to belong to a corresponding class. This classifier works on Bayes' theorem. In NB classifiers attributes are independent from each other on a given class. This assumption is known as class conditional independence [123].

Bayes theorem

Let $X = \{x_1, x_2, \ldots, x_n\}$ are total number of samples having some attributes and each sample belong to a specific class. In Bayesian terminology, X is considered as "evidence". Let H is a hypothesis and our objective is to find out $P(H|X)$ which is the probability of hypothesis H given the X. In other words, we can say that it is the probability that sample X belongs to class C. $P(H)$ is the prior probability of H and $P(H|X)$ is a posterior probability of H conditioned on X.

Classifier working

The naive Bayesian classifier works in the following way: let S be considered as a training set of samples, each of which are labeled with class labels. There is a total of k classes, $C_1, C_2, \ldots, C_k$ and n is the total number of samples $X = \{x_1, x_2, \ldots, x_n\}$. Consider an unseen sample X, the classifier will assign it to a class, to whom its posterior probability will be highest. In below mentioned condition, X belongs to C_i if, $P(C_i|X) > P(C_j|X)$ for any j different from i.

Thus the class that maximizes $P(C_i|X)$ will be selected as predicted class. The class C_i for which $P(C_i|X)$ is maximized is called the maximum posterior probability. By using Bayes theorem

$$P(C_i|X) = P(C_i)P(X|C_i)/P(X)$$

OR $$\text{Posterior} = \frac{\text{Prior} * \text{Likelihood}}{\text{Evidence}}$$

If the prior probability of class, $P(C_i)$, are unknown, then we take each class as equal, that is, $P(C_1) = P(C_2) = \ldots = P(C_k)$, and our goal will be to maximize the $P(X|C_i)$. Rather we maximize the $P(X|C_i)P(C_j)$. Class prior probability may be calculated by

$$P(C_i) = freq(C_i, S)/|S|$$

For a given problem to calculate the $P(X|C_i)$ following formula is applied

$$P(X|C_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right)$$

Where σ^2 and μ are the variance and mean of the sample belongs to class C_i and x is the value of test sample attributes. The probabilities $P(x_1|C_1)$, $P(x_2|C_2)$, . . . , $P(x_n|C_k)$ can be calculated from equation 3.14.

Naive bayes parameters: In this work, the NB method included a supervised discretization, to convert numeric attributes to nominal ones, as it considerably increased the performance of the algorithm [12].

4.2.5.4 Artificial Neural Network

An artificial neural network (ANN), a system of exploitation of the biological basis of neural networks is, in other words, an emulation of a biological neural system. The key objective of the development of an ANN is to develop a computation model which work like human brain and be able to solve hard problems in less computation time than traditional approaches [124].

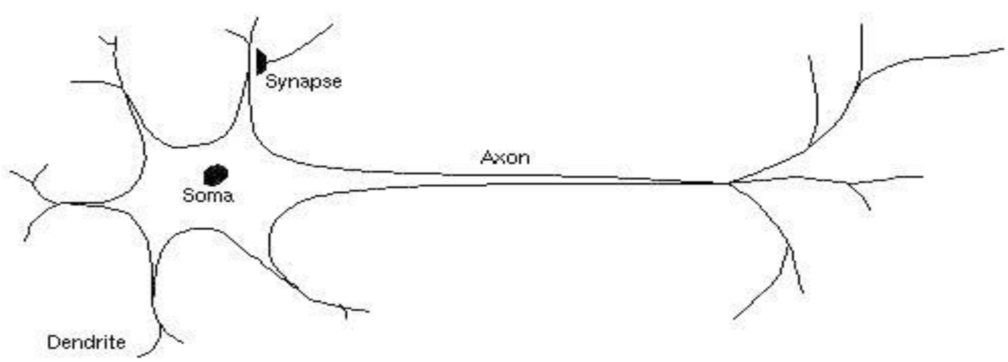

Figure 4-5 Biological Neuron

Neural networks show a remarkable ability to understand the meaning of complex or imprecise data, and can be used to extract patterns and detect trends that are too complex to be noticed by humans or other computer techniques. The first artificial neuron in 1943 produced by the neurophysiologist Warren McCulloch and the logician Walter Pits [124].

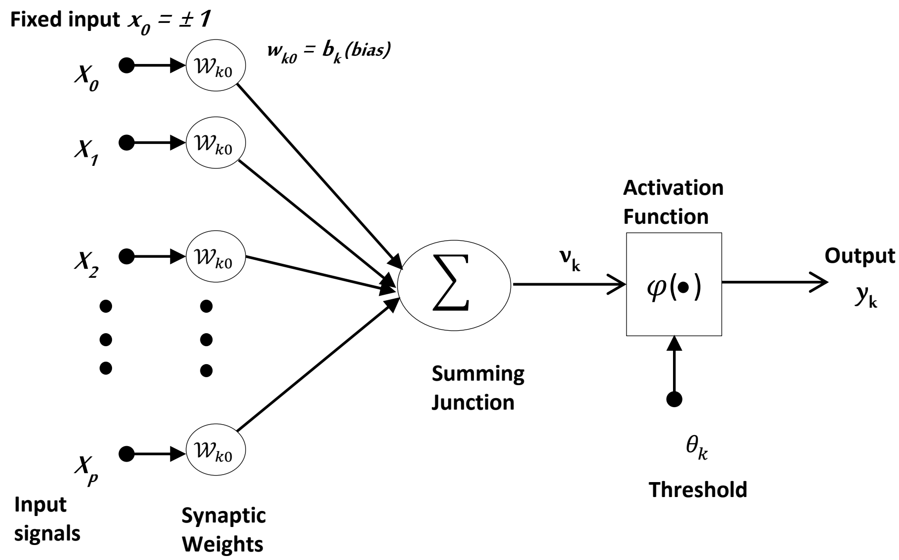

Figure 4-6 Structure of Perceptron

Artificial neural networks are useful to solve various problems like data clustering, optimization, pattern matching and classification. The structure of a neural network is like a directed graph in which different nodes, called neurons, in layers are connected to each other with some associated weights. Output of the neuron is determined through an activation function which is the sum of the product of inputs with their associated weight to that neuron [125]. ANNs are classified based on the number of layers: they can be single-layer or multilayer. Difference between single layer and multilayer networks is that in single layer networks the input layer neurons are directly connected to output layer neurons whereas in multilayer networks a few intermediate layers (named hidden layers) of neurons are present between input and output layers.

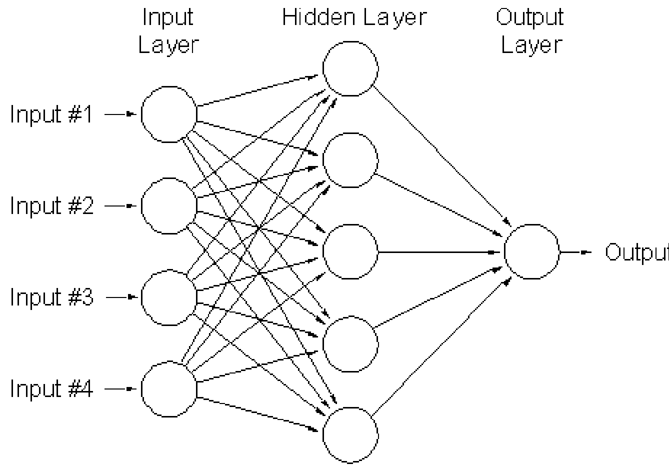

Figure 4-7 Multilayer ANN

Feed forward back propagation artificial neural network (FP-ANN) is one kind of multilayer ANN which is used for classification purposes using supervised learning. Training of network involves three phases. First is the feed forward of the training input pattern. Second phase is the calculation and back propagation of the associated error and third step is the adjustment of the weights such that reduced the classification errors. Once the network gets train it can be used for testing purpose [126].

ANN parameters: In the present work, a back propagation neural network with one hidden layer with 14 neurons and 500 training epochs provided the best results.

4.2.5.5 Decision Tree

Decision Trees (DT) are commonly used in classification problems using the concept of information gain or Gini gain [96]. A decision tree is a flow-chart-like structure, where each internal (non-leaf) node denotes a test on an attribute, each branch represents the outcome of a test, and each leaf (or terminal) node holds a class label. The topmost node in a tree is the root node. Training data in the tree is assumed to split on the basis of values of features that give maximum information gain.

DT parameters: In this study DT is implemented by using the best first tree (BFTree) learner where the best node is expanded first. The best node is the node whose split leads to the maximum reduction of impurity (Gini index) among all nodes available for splitting [96]. In this case, BFTree was evaluated by applying post pruning and a minimal number of 2 instances in the terminal node.

4.3 Conclusion

This chapter presented the state of the art in the activity recognition based on inertial sensors. Low computational preprocessing and segmentation techniques have been presented. Both time-domain and frequency-domain features were considered due to their high usability and performance in activity recognition studies. A variety of classification models including DT, NB, k-NN, SVM and ANN were selected. Use of these methodologies and their performance on the activity recognition studies are presented in the next coming Chapter 5.

5

Evaluation

This section presents the summary of the standard procedures that have been used to evaluate the accuracy of the activity recognition algorithms described in the previous chapter. Useful parameters which are important to consider but are usually neglected when evaluating the activity recognition algorithm are considered in this study. The first section of the chapter will present the measures used to evaluate the activity recognition algorithms. Results on the different methodologies adapted to recognize the daily living activities will be presented in the remaining sections.

5.1 Reporting and analyzing activity recognition results

This section describes which performance measures will be useful to evaluate the activity recognition algorithms implemented in this thesis.

5.1.1 Training and testing data requirement

It is believed that performance of the classification scheme depends on the amount and type (both subject-independent and subject-dependent) of the training data used. Both of them will be described in the following.

Subject-dependent validation

Previous studies in activity recognition suggested that many algorithms can perform well by using subject-specific training data. There are two commonly used ways to perform a subject-dependent validation. 1) One way is to perform n-fold cross validation; data from all participants were divided into n subsets, algorithms were trained on n-1 folds and tested on the remaining fold. This procedure is repeated n times, until all folds went through testing phase. Accuracy results are then generally calculated as the average over these n repetitions. The division of data into n folds is motivated by previous studies [12] [21]. 2) An alternative way is to divide a dataset into train and test sets, and assign data to either the training or to the testing, according to a specific percent split, usually set at 70 or 80 percent for training data and the remaining for test data. This procedure can be repeated by repeating the random assignment a number of times, and results from all iterations are averaged to obtain the final performance of the algorithms. The selection of the percentage spilt is tricky, as it depends on the size of the data samples.

Subject-independent validation

In the leave-one-subject-out cross validation, which is used to test the performance in the subject-independent case, the classifiers were trained on all the subjects except one, which was used for testing, and the procedure was repeated until all the subjects were used in the testing.

This thesis will evaluate the performance of the developed algorithms on both subject-dependent and subject-independent validation. Performance on validation techniques will be reported in terms of overall accuracy across multiple activities, and in terms of accuracy per activity. Additionally, in subject-dependent validation different percentages of the training data will be used to find the appropriate percentage that needs to be used to optimize classification performance.

5.1.2 Algorithm efficiency constraints

Some other constraints related to the efficiency of the recognition algorithms to be considered in the study are associated with the possibility to have a real-time classification of activities, instead of offline processing. In these conditions, the following are the points to be taken into account:

Real-time recognition delay: Some real-time recognition algorithms introduce delay between activity occurrence and detection. Shorter recognition delays may allow for better point of decision interventions.

Real-time recognition of activities: An algorithm capable of recognizing activities in real-time, must be light in terms of computational complexity, in such a way that it may be run on reduced resources for computing (mobile phones, smartwatches, bracelets, …).

5.1.3 Performance measures

The performance of the activity recognition algorithms will be evaluated by calculating commonly used evaluation matrices in activity recognition, such as: average accuracy, confusion matrix, sensitivity and specificity of each activity class. These are calculated as:

$$Accuracy = \frac{Correct\ predictions}{N}$$

$$Sensitivity_i = \frac{TP_i}{TP_i + FN_i}$$

$$Specificity = \frac{TN_i}{TN_i + FP_i}$$

Where N is the total number of samples, TP_i is the true positive or truly classified samples of the class, FN_i indicates the false negative or misclassified samples of the class i, FP_i indicates the false positive or wrong predictions. Sensitivity and specificity represents the recall and precision of the class.

5.2 Sliding window based segmentation on the classification of daily living activities including transition activities

5.2.1 Study contribution

This study will investigate the impact of different window sizes on activity recognition, some activities that had short time duration (sit to stand, sitting, stand to sit and standing, all in the range 1-6 s) will be considered. In this way, a total of six different classes are defined: Stair descending, Stair ascending, Walking, Sitting, Standing, and one class is including all transitions between the previous five activities. Recognizing these activities is challenging when a single sensor is placed at the waist level, as they are highly similar in postural patterns (sit and stand)

and movement patterns (walking and stairs walking). By including transitions, it will be possible to determine whether the natural increase in accuracy corresponding to higher window size is counteracted by a decline in performance associated with transition misclassification. However, literature is scarce on the investigation of the effect of window size on classification accuracy of activities including transitions. The study will also evaluate the different percentages of training data splits to access the classifiers performance and hence suggests the desirable amount of percentage to be considered.

5.2.2 Signal segmentation and feature extraction

At first, the acceleration data stream underwent low-pass filtering (Butterworth, fifth order, cutoff frequency 18 Hz). Then, data are segmented using sliding windows of different size (0.5 s, 1s, 1.5 s, 2 s, 2.5 s and 3 s) to find out its effect on the daily living activity classification. Windowed data are labeled based on the ground truth knowledge of the activities: when dealing with more than one activity within a window, this is labeled by considering the activity that was more present within that window.

For each windowed data, a feature vector is calculated, with the following 22 time-based components:

- Mean value along each axis, and average of mean values along the three axes
- Standard deviation value along each axis, and average of the standard deviation values along the three axes
- Skewness for each axis, and average of the skewness values along the three axes;
- Kurtosis for each axis, and average of the kurtoses along the three axes
- Correlation at zero lag between each axis pair, and between each axis and the magnitude acceleration.

These features are chosen based on the consideration that computational complexity associated with their extraction is not demanding, thus making them easier to be used in a real-time scenario, as compared to frequency domain features.

5.2.3 Classification models and performance evaluation

In this work, five different classification methods; DT, k-NN, NB, SVM and ANN are used, to check the behavior of the classifiers among different window sizes. The parameters of each classifier are configured heuristically to achieve the highest recognition rate, as mentioned in section 4.2.

The classifiers performance is evaluated through both subject-dependent and subject-independent formulations. In the subject-dependent case, two different criteria to split the dataset into training and test are considered and independently tested:

1) To perform the training of each classifier on the same amount of data samples across different window sizes, different percentages of the overall dataset are considered (12%, 23%, 35%, 46%, 58% and 70% of training data for 0.5, 1, 1.5, 2, 2.5 and 3 seconds of windows, respectively). In this way, it is possible to minimize the bias associated with having classifiers trained on different set sizes.
2) To evaluate the accuracy of the classifiers on a balanced share between test and training, the training set is fixed at 70% of the overall dataset for each window size.

In both cases, average accuracy is calculated both with Cohen's kappa coefficient. Analysis of variance (ANOVA) and post-hoc Bonferroni tests are then performed to check for significance in classification accuracy differences among window size pairs.

5.2.4 Results

For each of the classifiers, results are reported in terms of the overall accuracy obtained for the proposed 6 different window sizes: 0.5 s, 1 s, 1.5 s, 2 s, 2.5 s and 3 s. Values are reported for the subject-dependent case first, and then for the subject-independent validation one.

5.2.4.1 Subject-dependent validation with different percentage split

Figure 5-1 shows the average classification accuracy for the different classifiers across the different window sizes, both for the same training sample size criterion, and for the 70%-30% split criterion. For each classifier-window size configuration, 10 randomized iterations were run.

In the subject-dependent case, a very reduced variation in accuracy appeared among the window sizes (1-3 s) and among classifiers, when the same amount of data for training is used. By using the 70%-30% split criterion, the accuracy of all the classifiers increased, especially for the smaller window size (0.5 s). To better understand the accuracy of the classifiers and the effect of the window size, Cohen's kappa coefficient is also reported in figure 5-2.

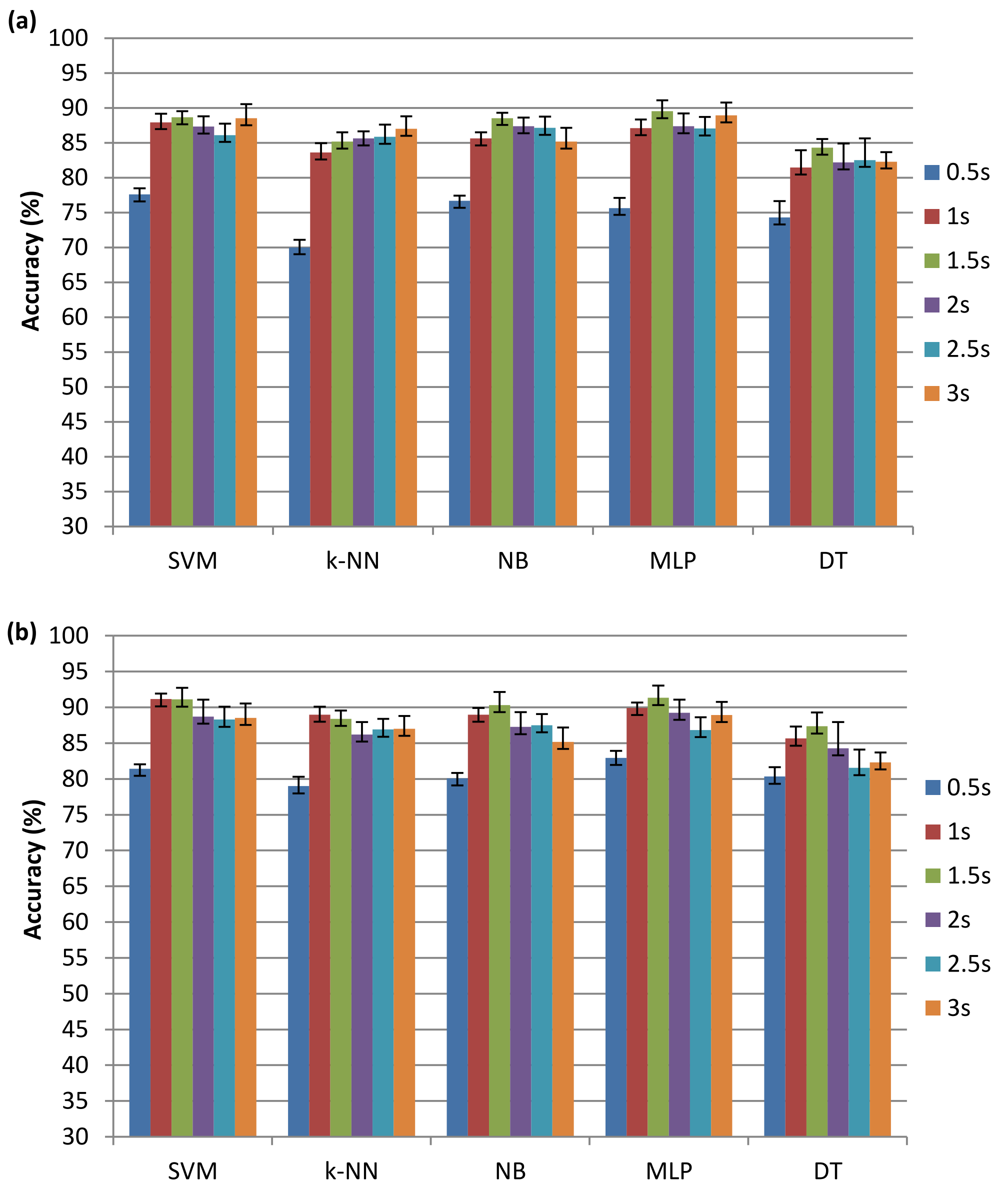

Figure 5-1 Average classification accuracy (and standard deviation) for the subject-dependent case: (a) Same sample size for training criterion, and (b) 70–30% split.

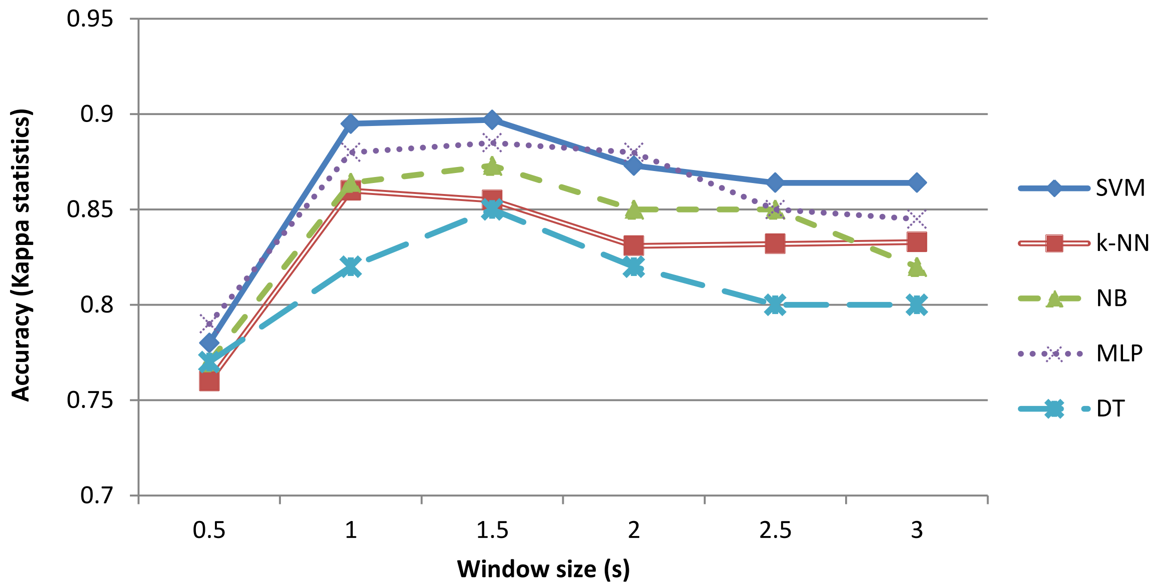

Figure 5-2 Cohen's kappa coefficient: classifier VS window size.

From the kappa statistics results of the subject-dependent case, it has seen that the majority of the classifiers reached their peak accuracy with the 1.5 s window sizes, with a negligible difference in accuracy between 1 s and 1.5 s in most of them. In general terms, SVM performance is the highest, with MLP and NB very close.

Table 5-1 Analysis of variance in response to different window sizes and training split settings.

SAME SAMPLE SIZE

SVM	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	ns				
2	+	ns	ns			
2.5	+	ns	-	ns		
3	+	ns	ns	ns	+	

k-NN	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	ns				
2	+	+	ns			
2.5	+	+	ns	ns		
3	+	+	ns	ns	ns	

NB	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	+				
2	+	+	ns			
2.5	+	ns	ns	ns		
3	+	ns	-	-	-	

MLP	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	+				
2	+	ns	-			
2.5	+	ns	-	ns		
3	+	ns	ns	ns	ns	

DT	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	ns				
2	+	ns	ns			
2.5	+	ns	ns	ns		
	+	ns	ns	ns	ns	

70% - 30% SPLIT

SVM	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	ns				
2	+	-	-			
2.5	+	-	-	ns		
3	+	-	-	ns	ns	

k-NN	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	ns				
2	+	-	-			
2.5	+	-	ns	ns		
3	+	-	ns	ns	ns	

NB	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	ns				
2	+	ns	-			
2.5	+	ns	-	ns		
3	+	-	-	ns	-	

MLP	0.5	1	1.5	2	2.5	3
0.5						
1	+					
1.5	+	ns				
2	+	ns	-			
2.5	+	-	-	-		
3	+	ns	-	ns	+	

DT	0.5	1	1.5	2	2.5	3
	+					
	+	ns				
	+	ns	-			
	ns	-	-	ns		
	ns	-	-	ns	ns	

ns, not significant difference (p _ 0.05); +, positive significant difference (i.e. the classification accuracy of the window size defined in the row is significantly higher than that in the column, $p < 0.05$); −, negative significant difference (i.e. the classification accuracy of the window size defined in the row is significantly lower than that in the column, $p < 0.05$).

Table 5-1 shows the results of the ANOVA analysis for both criteria. 0.5s window size performs significantly worse than any other window size for virtually every classifier-splitting criterion. 1.5s window size is never significantly worse than any other window size for every classifier splitting criterion, and it is significantly better than 1.0s in both NB-same sample size and MLP-same sample size combinations (for the other combinations, there is no significant difference between 1.0s and 1.5s). When a difference appeared, larger window sizes resulted significantly worse than 1.5s in a number of different combinations: 70%-30% for both k-NN, SVM, and DT; same sample size for MLP. 1.0s window had, on average, mixed results, as compared to window sizes larger than 1.5s: it performed significantly better for a number of different combinations (70%-30% for SVM , k-NN, and DT), and worse for some other ones in the same sample size splitting (k-NN and NB as compared to 2s).

Table 5-2 Confusion matrices obtained for the different window sizes for the SVM classifier. Values in bracket represent the number of records.

	Confusion Matrix												
	0.5 s						**1 s**						
Predicted / Actual	*SD%*	*SA %*	*Walk %*	*Sit %*	*Stand %*	*Trans %*		*SD %*	*SA %*	*Walk %*	*Sit %*	*Stand %*	*Trans %*
SD (563)	**68.4**	3.9	20.1	0	2.1	5.5	***→(182)***	**93.9**	1.1	4.4	0	0	0.6
SA (609)	1.8	**76.5**	15.1	0	0.7	5.9	***→(210)***	0.9	**92.4**	6.2	0	0	0.5
Walk (721)	9.0	6.1	**78.5**	0	0.3	6.1	***→(397)***	6.0	7.1	**83.1**	0	0	3.8
Sit (286)	2.4	0	3.2	**89.5**	0	4.9	***→(113)***	0	0	0	**97.3**	0	2.7
Stand (321)	0	0	0	0	**99.1**	0.9	***→(138)***	0	0	0	0.7	**96.4**	2.9
Trans (516)	8.2	11.4	3.9	2.3	6.9	**67.3**	***→(220)***	1.4	3.6	2.3	5	6.8	**80.9**
	1.5 s						**2 s**						
SD (107)	**91.6**	0.9	5.6	0	0	1.9	***→(56)***	**89.3**	1.8	7.1	0	0	18
SA (140)	2.1	**90.8**	5.7	0	0	1.4	***→(76)***	0	**93.4**	5.3	0	0	1.3
Walk (198)	6.1	6.6	**82.3**	0	0	5.0	***(139)***	5.8	4.3	**88.5**	0	0	1.4
Sit (56)	0	0	0	**89.3**	0	10.7	***→(21)***	0	0	0	**90.5**	0	9.5
Stand (69)	0	0	0	1.4	**89.9**	8.7	***→(47)***	0	0	2.1	0	**89.4**	8.5
Trans (144)	2.8	0.7	0.6	2.8	0.7	**92.4**	***→(96)***	3.1	1.1	6.2	7.3	3.1	**79.2**
	2.5 s						**3 s**						
SD (42)	**88.1**	2.4	9.5	0	0	0	***→(29)***	**89.6**	3.4	6.9	0	0	0
SA (44)	0	**88.6**	11.4	0	0	0	***→(27)***	0	**96.3**	3.7	0	0	0
Walk (79)	3.8	2.5	**89.9**	0	0	3.8	***→(42)***	0	4.8	**92.8**	0	0	2.4
Sit (14)	0	0	0	**78.6**	0	21.4	***→(8)***	0	0	0	**62.5**	0	37.5
Stand (23)	0	0	0	0	**69.6**	30.4	***→(18)***	0	0	0	0	**61.1**	38.9
Trans (69)	0	0	0	10.2	2.9	**86.9**	***→(37)***	0	0	0	13.5	10.8	**75.7**

Stairs Descending (SD), Stairs Ascending (SA), Walking (Walk), Sitting (Sit), Standing (Stand), Transitions (Trans)

To check where misclassifications appeared most frequently, Table 5-2 reports the normalized values of the confusion matrices for the classifier that performed best across the different window sizes. As expected, variations in accuracy appeared among different window sizes, with transitions being most often misclassified. Choosing a 1 to 2 s window size represents a good trade-off, as with these window sizes misclassifications among transition and other dynamic activities are reduced, and their percentage roughly corresponds to the percentage of the first and last occurrence steps of each activity. With higher window sizes, the performance decreases, misclassifying short duration activities for transitions, while with 0.5 s many transitions are misclassified for a variety of different static and dynamic activities.

Figure 5-3 exemplifies the effect of the segmentation obtained with a 1 s and a 3 s sliding window over a short duration activity signal sample: in this case, with a 3 s window size the transition activity is classified as a static activity due to the uneven window data distribution. While looking at 1 s window performance, misclassification chance is virtually limited to conditions when an activity starts or ends. As the size of the 1 s window is small compared to the window activity durations, there is higher chance of having the window falling between the start and the end of an activity.

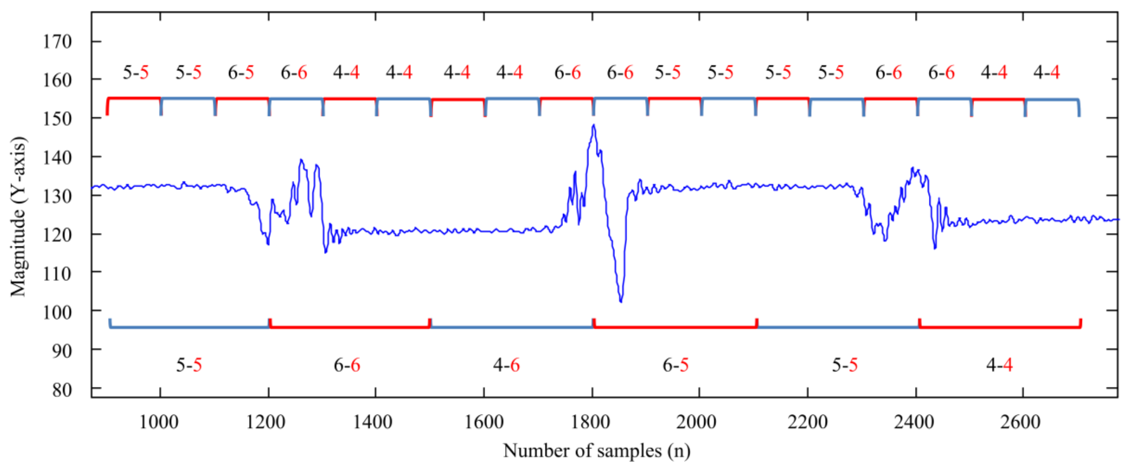

Figure 5-3 Sample of acceleration data corresponding to a sequence of activities, together with target activities (black), and SVM classification outputs (red), for both 1s window size (upper line), and 3s window size (lower line). 4 corresponds to sitting, 5 to standing and 6 to transitions.

5.2.4.2 Subject-independent validation

Figure 5-4 shows the classification accuracy for the different window sizes, across the different classifiers, as averaged across the 9 iterations corresponding to the subjects left out in the subject-independent case.

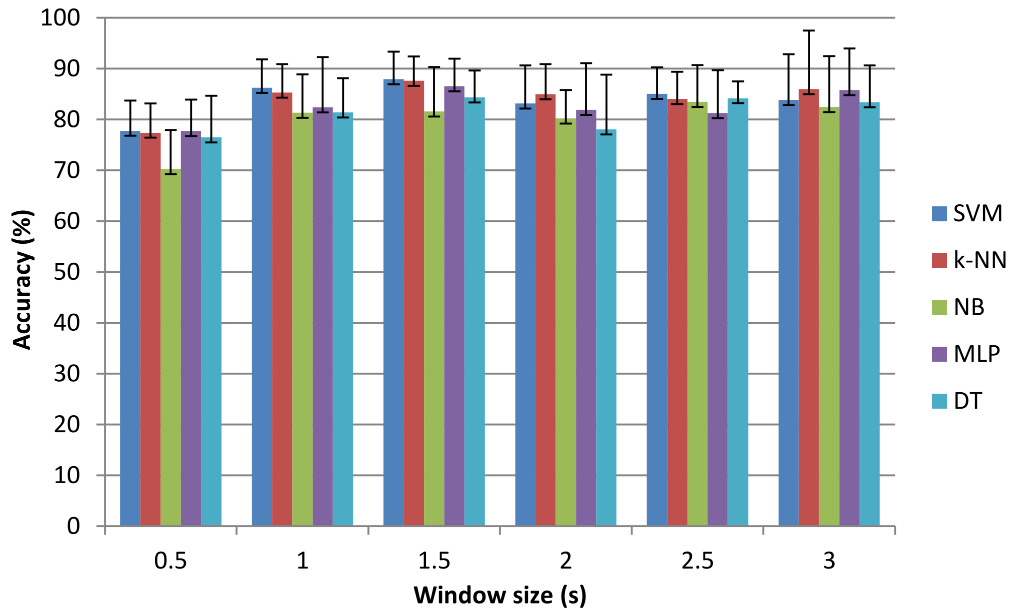

Figure 5-4 Average classification accuracy (%) on subject-independent validation. Standard deviation is also reported.

Here all classifiers consistently reached their highest accuracy with a 1.5 s window size, followed by 1 s and 3 s, respectively. In the 3 s window size, accuracy among the subjects varies, with an increase in the standard deviation. Among the classifiers, SVM performance performed best, followed by k-NN and MLP in 1.5 and 1 s of window, whereas MLP classifier shows an increased variability in accuracy among the subjects.

5.2.5 Discussion and conclusion

The impact of window size on the activity recognition problem was investigated to identify a window size that may prove optimal in real-time recognition of human activities. While considering this aspect, combinations of static, dynamic, and short duration activities were included. The use of longer windows might be a good choice to classify among long duration activities, but the behavior varies if short duration activities are considered, and transitions, which were here considered as a separate class to be detected, and not discarded.

Most classifiers reached their peak accuracy with either 1 or 1.5 s window size, with 1.5 s appearing most often. With these window sizes, in subject-dependent validation, the highest accuracy was achieved by SVM (accuracies > 90%) followed by MLP and NB, with accuracies just a few percentage points lower. In subject-independent validation, the performance of classifiers varied from subject to subject, with the average performance of SVM being high (values > 87.5%) and better than the other classifiers (both for 1 s and 1.5 s), with kNN and MLP respectively following. These latter results are in accordance with Cleland et al [12] who showed that SVM performs most accurately with data coming from a single location.

It can be also speculated that, in subject-independent validation, SVM and kNN are better able to deal with variability in activity durations, as the participants of this experimental testing were asked to perform activities at their self-defined speed, and some participants chose a very high speed. It is here to be highlighted that, in other studies, results were different: in [21] MLP achieved highest accuracy while applying 10-fold cross-validation technique; while in [81] SVM achieved highest accuracy where subject-independent validation was applied.

While the focus of this work was not that of finding the best performing classification technique, overall accuracy results achieved in this study are in line, in some cases lower than those obtained in previous similar studies: this may be due to the type and duration of the activities investigated in the study, where the data were collected and labeled with a specific class associated with transitions. This was done also to verify whether it was possible to identify a window size for segmentation that provided optimal results in a real-time scenario. A number of limitations for this study are: first, the amount of participants prevented us from capturing inter-individual differences associated with different posture and locomotion styles. In these regards, the leave-one-subject out approach was specifically chosen to take this into account. Then, the recruited participants were young adults, and it might be possible that elderly people, who may choose reduced speeds, might lead to differences in classification accuracy.

5.2.5.1 Final considerations for training data amount

Results reported above were based on two different percentage splits for training data; in first case, to avoid any biasness, classifiers were trained over the same amount of data (SAD) (i.e. 12%, 23%, 35%, 46%, 58% and 70% for 0.5s, 1s, 1.5s, 2s, 2.5s and 3s windows respectively), whereas in second case, classifiers were trained over the same amount of percentage split for each window size that is 70% of the data. Based on these settings, it has been found that accuracy over 0.5s, 1s and 1.5s windows increases when moving from SAD split to 70% split, this happens because, for these windows, a training set composed of 12%, 23% and 35% of overall data to train classifiers is not a sufficient amount as compared to other windows which is around 50% to 70%. To check at which percentage split point the accuracy doesn't increase sufficiently, another split of 50% is added to 0.5s, 1s, 1.5s and 3s of windows which is close enough to 46% and 58% for 2s and 2.5s of window for comparison. Table 5-3 elaborates the results on different training data splits over three best classifiers ranked by Cohen's Kappa results.

Table 5-3 Comparison of classification accuracy obtained on different training data splits.

Classifiers	**Window size (s)**	**Training data splits**		
		SAD	***50%***	***70%***
SVM	0.5	77.6	82.5	81.44
	1	87.9	90.87	91.15
	1.5	88.67	89.75	91.1
	2	87.34	87.34	88.73
	2.5	86.12	86.12	88.29
	3	88.53	86.9	88.53
NB	0.5	76.6	79.2	80.09
	1	85.6	87.7	88.9
	1.5	88.5	89.2	90.32
	2	87.3	87.3	87.2
	2.5	87.1	87.1	87.5
	3	85.17	84.8	85.17
MLP	0.5	75.6	82.4	82.9
	1	87.1	89.2	89.9
	1.5	89.5	90.2	91.3
	2	87.37	89.26	89.26
	2.5	87.07	86.8	86.8
	3	88.92	87.47	88.92

SAD: 12%, 23%, 35%, 46%, 58% and 70% for 0.5s, 1s, 1.5s, 2s, 2.5s and 3s windows respectively

Results reported in the table show that the increase in accuracy from 50% to 70% is negligible over all the windows. Whereas for 0.5s and 1s windows accuracy increases from SAD split to 50% split. In 1.5s and 3s windows there is no significant difference between SAD split and 50% split. Difference between SAD split and 70% split is negligible in 2s and 2.5s windows and hence doesn't produces much increase in accuracy. It is found that the amount of data used to train classifiers should be 50% to 70%, depending on the size of the overall data.

5.2.5.2 Final considerations for window size

Results of the study suggest that the use of 1.5 s (and in some cases, 1.0 s) window can accurately classify static, dynamic, and transitions activities considering both short and long duration ones. Shorter window sizes might be helpful in classifying between static and dynamic activities, but fail if it is required to distinguish among dynamic activities: in effect, this temporal support does not sufficiently capture data differences coming from the varying behavior of the dynamic activities. Longer window sizes respond well on long duration dynamic activities, but this is counteracted by an increased misclassification rate for short duration activities. Also, larger window sizes provide decreased accuracy when dealing with transitions, and the delay in real-time human activity recognition may be relevant.

In conclusion, the findings of this work suggest some guidelines for window size selection to classify daily living activities: 1.5 s time window could be considered for timely detection over short and long duration dynamic activities and static activities. Further work may be required: 1) to find additional features to increase the accuracy of the system on the chosen window size; 2) to check whether it would be possible to have a time-varying window size to increase accuracy; and 3) to apply meta-level classification methods to improve classifier behavior.

5.3 Comparison between event-based and sliding window segmentation on locomotion activity classification

5.3.1 Contribution

This study presents the implementation of an event-based dynamic segmentation algorithm to identify the gait events of locomotion activities from a shank mounted inertial sensor. It then analyses and compares the classification accuracy obtained through the proposed event-based dynamic segmentation against different fixed window lengths, on the classification of daily living activities, including walking, stair ascent, stair descent and running. In order to tune the event detection to these locomotion activities (that were not limited to level walking, but included stair negotiation), the gait detection criterion is modified in such a way that no window is explicitly used to detect the events. Then these events are used to define a signal segment that represents the whole gait cycle, to be used for the classification of locomotion activities. A benchmark dataset has been also used to validate the segmentation technique. For the details regarding the dataset, please refer to [127].

5.3.2 Event-based signal segmentation

The event-based signal segmentation algorithm that is described in section 4.2 has been used in this study to segment the gait cycle. Different locomotion activities: walking, stairs descent, stairs ascent and running have some common characteristics like swing phase, stance phase etc. The shape of the swing phase (maximum peak) in the gyroscope signal has consistency throughout the signal followed by the lower peak of the stance phase. Each activity cycle for this activity subset is composed of a swing phase and a stance phase, and they can be identified by considering mid-swing (MS), initial contact (IC), and end contact (EC) events. There is mutual agreement that foot-off event can be detected by identifying the minimum value of the negative peak before swing phase peak and this foot-off event is used to identify the start and end of the gait cycle [62].

In this study, the algorithm detected these three events to find a single cycle from the raw gyroscope angular component along the sagittal plane. The segmentation is called real-time as it is done by sample by sample evaluation to detect the gait events. The whole procedure for event detection is defined in Table 5-4 and the outcome of the algorithm over the signal is shown in figure 5-5.

Each activity cycle (segment) is then defined by using consecutive EC events. For comparison, also fixed length widows were considered (with values of the window length equal to 1, 1.25 and 1.5 s, respectively).

Table 5-4 Heuristic rules for the activity event detection

Activity Events	Rules
Mid-swing (MS)	MS detection is based on four conditions i. Find zero crossing when the signal is ascending (negative-cross) ii. Update maximum value just after the above condition meet iii. Find zero crossing when signal is descending (positive-cross) ***If*** Maximum value between two crossing ≥ 2 rad/s **then** **save** negative-cross, positive-cross (current value) and mid-swing (maximum value) ***else*** search zero cross in ascending
Initial contact (IC)	IC is detected as the minimum just after the positive-cross **When** current value fulfill this condition: i. $y(j) > y(j-1)$ Then, $IC = y(j)$
End contact (EC)	First minimum value is min_value = IC Algorithm starts searching for max_value and min_value. **Max_value condition:** $y(j) < y(j-1)$ && $diff(min\_index \;\; j) \geq 6$ $max\_value = y(j)$ **Min_value condition:** $y(j) > y(j-1)$ $min\_value = y(j)$ If the current value $y(j)$ is min_value then algorithm goto **EC condition:** $diff([max\_index \;\; min\_index]) \geq 6$ && $min\_value \leq 1.4\, rad/s$ && $diff\ ([min\_index\_array\,(1)\ max\_index]) \geq 7$ ***If*** above condition is satisfied **then** $EC = y(j)$ ***else*** update local minimum & maximum and meet the EC condition.

y(j) is the current value of the gyroscope, min_index and max_index are the indices of min & max values, min_index_array(1) is the index of the 1st minimum value, representing IC.

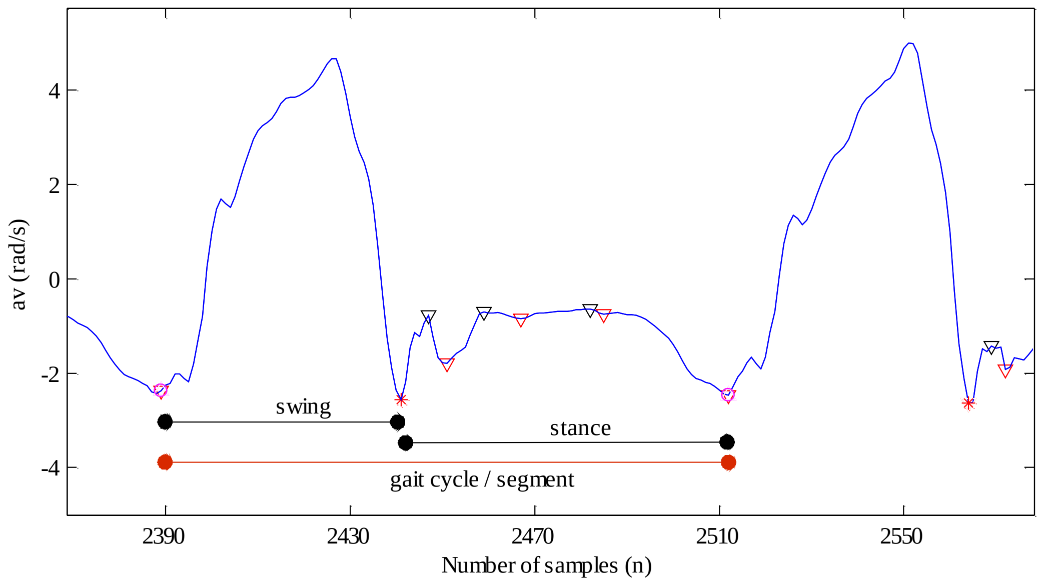

Figure 5-5 Segmentation algorithm detection for a walking step, where black and red triangles are t_{max} and t_{min}, red asterisks are foot strike and pink circles are foot off events.

5.3.3 Feature set based on Linear Forward Feature Selection (LFFS) technique

Segments identified with the above-mentioned rules are taken as the reference for all the remaining inertial data. For each segment, a set of time and frequency domain features that are used in the literature for the activity recognition problem are derived from each axis and magnitude of the accelerometer and gyroscope raw signal. A total number of 138 features are then extracted.

LFFS technique is used to remove the redundant features from the whole feature space. Algorithm starts from the empty set and sequentially adds the feature x to the set which maximizes the objective function of the previously added features. Selected features are mentioned in Table 5-5. A total number of 30 features (FS1) have been selected by the algorithm from BioLab³ dataset, and 24 features (FS2) from PAMAP2 dataset.

Table 5-5 Selected features from accelerometer (a) and gyroscope (g) for the two feature sets.

Features	FS1	FS2
Time domain		
Mean	A (x, y, mag)	A (y, mag), G (mag)
Median	A (y), G (y, z)	
St. deviation	A (x, y), G (z)	G (z)
Skewness	A (z), G (z)	A (y), G (z)
Kurtosis		
Correlation	A (x_z, x_mag), G (x_mag, y_mag, z_mag)	A (y_mag), G (x_z, x_mag, z_mag)
Inverse cosine		G (x)
Interquartile range		A (y), G (x)
Frequency domain		
Mean	A (mag)	A (mag), G (mag)
Median		
St. deviation	A (x, y), G (mag)	A (mag), G (mag)
Skewness	G (x)	G (mag)
Kurtosis	G (z)	A (mag)
Energy	A (x)	G (z)
1st five FFT components	A_x (2), A_y (2,5), G_y (4), G_z (1, 2, 4)	G_z (2, 3, 4, 5)

In this study, two feature sets FS1 and FS2 for each dataset are selected. The purpose of selecting features from different datasets is to check whether the selection on one dataset would affect the classification accuracy rate of the other dataset respectively, as the position of the sensors in the two datasets was slightly different.

Features extracted from each segment are passed to the MLP to classify the activity, where each segment (gait cycle) is classified as either walking, stairs ascend, stairs descend or running activity. A leave-one-subject-out cross-validation criterion is used to evaluate the performance of the classifier.

5.3.4 Use of benchmark dataset (PAMAP2 dataset)

The PAMAP2 benchmark dataset is also used to check the validity of the method. This dataset is composed of different activities from 9 participants. For the purposes of this study, only those activities have been selected that could be compared with the other database of interest (walking, stair ascent, stair descent and running). Data coming from the ankle-mounted sensor (a tri-axial accelerometer and a tri-axial gyroscope) is used, which is at a slightly lower position as compared to the sensor position used in the BioLab³ dataset. Further information about the dataset is available [127].

5.3.5 Results

5.3.5.1 Performance of dynamic segmentation technique

Figure 5-6 shows a sample of the results of the event-based segmentation algorithm over walking, stairs ascend, stairs descend and running activities. As it can be seen, events are detected accurately, with a limited variation depending on the activity type.

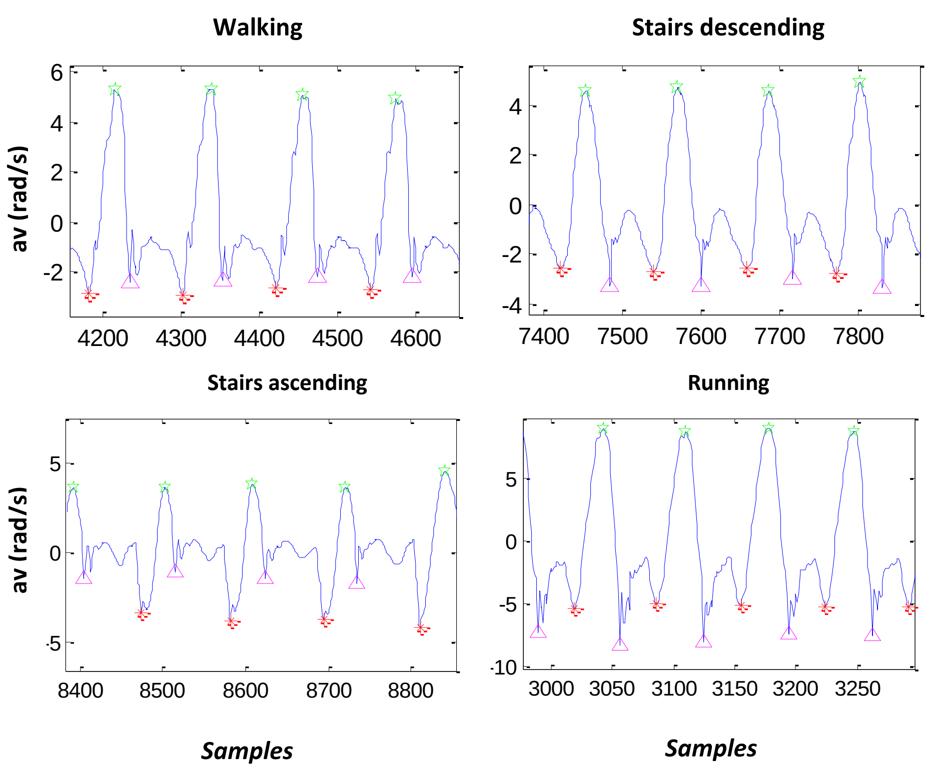

Figure 5-6 Gait events detection over four locomotors activities, where green, pink and red points represent MS, IC and EC respectively.

In particular, the algorithm mis-detected only 5 activity cycles (out of 1752): among them, one walking and one stairs ascend cycle is not identified because of lower MS; in one walking, stairs ascend and stairs descend cycle EC are not identified. All the running activity cycles are correctly identified.

5.3.5.2 Classification accuracy on static and dynamic segmentation

Choice of the fixed length window for comparison

In order to understand the performance of the dynamic window (gait cycle), the activity classification accuracy obtained from features extracted with the event-based segmentation technique are compared with the ones extracted with different sizes of the fixed length window. For a fair comparison, sizes of the fixed length window are selected on the basis of the average activity cycle duration, and in such a way that the overall number of records would be similar to the number of records extracted from the event-based segmentation technique. Table 5-6 reports the average activity cycle duration as estimated with the segmentation technique, and the number of records that are used with the event-based segmentation and the different fixed length segmentation values.

Table 5-6 Activity cycle duration over different activities.

Measures	**Activity cycle duration (s)**			
	Walk	*SD*	*SA*	*Run*
Mean	1.165	1.134	1.24	0.719
St. deviation	0.101	0.143	0.158	0.035
	Windows			
	1 s	*1.25 s*	*1.5 s*	*Dynamic*
No. of records	1994	1583	1320	1752

Readings show variations in activity cycle duration within the activities and within the subjects and none of the activity last for 1.5 s (100 samples /s). On the basis of the number of records (extracted window), comparison between the dynamic, 1 s and 1.25 s windows would be more interesting, as the number of records is similar to the ones of the dynamic segmentation.

Activity classification accuracy results will be reported into two different sections, corresponding to the two different datasets.

Performance on BioLab³ dataset

Figure 5-7 shows that the average performance of the dynamic window is higher than all static windows in both cases.

Classification performance of the dynamic window on FS1 and FS2 is pretty high (> 95% and > 90%, respectively), with less variation among the subjects. Whereas, accuracy obtained on 1s and 1.25 s windows is less than 90%, giving high variation among the subjects. 1.5 s window performance is high from the rest of the static windows but a significant difference from dynamic window.

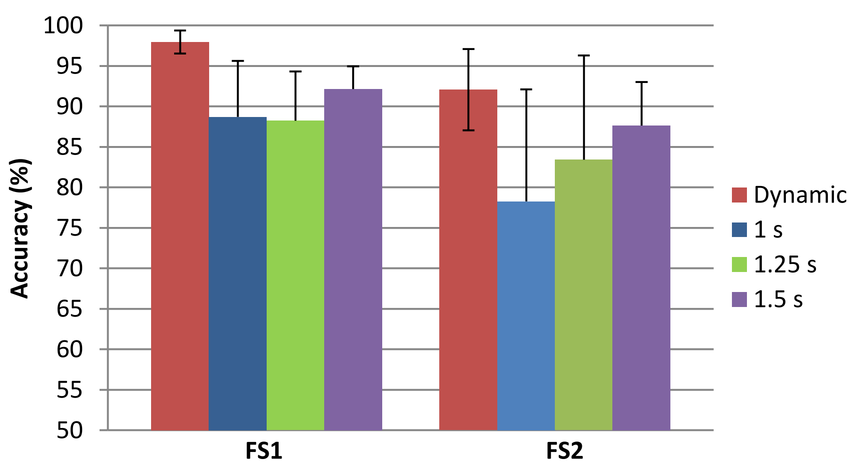

Figure 5-7 Classification accuracy for BioLab³ dataset.

Performance on PAMAP2 dataset

For the benchmark dataset, performance on different segmentation methods is less than 90% on FS1 while on FS2 accuracy increases significantly. Figure 5-8 shows the classification accuracy on PAMAP2 dataset.

Event-based dynamic segmentation performs slightly better than 1.5 s fixed window size window with both feature sets, and it is associated with a slightly higher variability than 1.5 s window size for FS1.

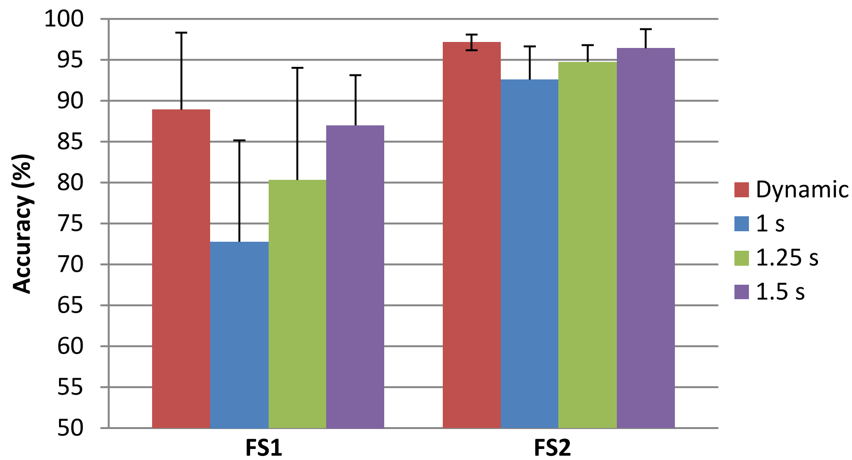

Figure 5-8 Classification accuracy for PAMAP2 dataset.

In regards to the datasets, classification accuracy was shown to depend on the feature set. As the sensor position is different in the two used datasets, feature set obtained on one dataset might be not good enough to represent the information for the other one. In the BioLab³ dataset, however, the average accuracy obtained with both feature sets has been shown to be higher than 90% for the event-based segmentation.

5.3.6 Discussion and conclusion

We evaluated the activity recognition performance on two datasets with different segmentation methods and feature sets. Four different locomotion activities are targeted in the dataset that are also present in the benchmark dataset.

It is found that the proposed event-based dynamic segmentation technique correctly identifies almost all the activity events (> 99% in both datasets). Catalfamo et al. algorithm detected more than 98% correct events in level and incline walking [77] and Formento et al. obtained values higher than 93% in stairs walking [128]. Salarian et al. found 100% correct gait events in walking activity, where algorithm detects swing phase peak and find initial and end contact events within backward and forward windows from swing peak [62] and similar method is used in [31]. All mentioned studies detect the events based on small windows and only Chen et al classified the activities and reported average accuracy higher than 93% [31]. Regarding the classification results, performance of the neural network on the proposed event-based dynamic segmentation is higher (> 95%) than that obtained with the relevant fixed window sizes. While a number of studies encouraged the use of fixed window size segmentation for activity recognition problem, the results obtained in this work seem to go in the other direction, as these results are better than the ones obtained by Hong et al. [15] (93.78%), Lee et al. [26] (86-92%, with 10 s of window size) and Wang et al. (93.3%) [129]. Fixed window size can thus be sub-optimal when activities last for significantly shorter or longer time periods than the window length, or when activity durations vary over time. To compensate for this problem, event-based dynamic segmentation is a viable solution, if it is sufficiently accurate in detecting events.

5.4 Pre-Processing Effect on the Accuracy of Event-Based Activity Segmentation and Classification through Inertial Sensors

5.4.1 Contribution

This study analyzes and compares the classification accuracy obtained through an event-based dynamic segmentation on different pre-processing operations. In particular, since the goal of this work is to assist the researcher in building real-time applications, the monitored pre-processing operations will be considered, taking into account the computational complexity associated with their implementation. The main contribution of the study is thus:

- to investigate whether, and to what extent, de-noising and inclination correction pre-processing has an effect on the dynamic segmentation of activities and on the subsequent classification accuracy.

5.4.2 Study design

In order to evaluate the segmentation accuracy across different datasets, Biolab[2] and Biolab[3] datasets are used. Flowchart of the activity recognition algorithm is shown in figure 5-9.

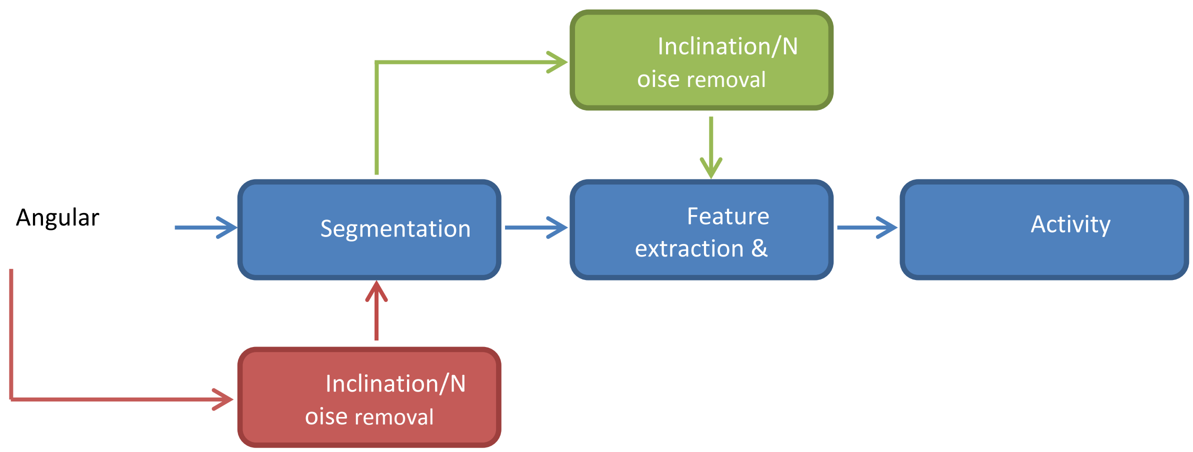

Figure 5-9 Work flow of the activity recognition chain.

5.4.2.1 Feature set used for classification

A total number of 152 features are thus extracted from the segments obtained from dynamic segmentation algorithm (section 4.2). Feature selection is done through the SVM classifier, where attributes are ranked by the square of the weight assigned by the SVM [130], and the first 20 features are selected based on the experiments to classify the activities. The selected features are listed in Table 5-7.

Table 5-7 SVM selected features.

Features	**Time domain**	**Frequency domain**
Mean	a_x, a_y	
Median	a_y, g_z, g_{mag}	
Skewness	a_z	g_z
Standard deviation	a_x, a_y	
Correlation	$g_{z,mag}$	
Interquartile	g_z	
Energy		a_x
FFT coefficients		$a_x(2)$, $a_y(1,2,3,5)$, $a_{mag}(1,2)$, $g_z(3)$

The first five FFT coefficients (as calculated over 100 samples) are used, as these contain the main frequency components (up to 5 Hz). The features selected by the algorithm are also used in other studies [25] [131] and are considered useful for running on smartphones, as they have very low to low computational and storage complexity.

Figure 5-10 shows the activity cluster representation for a subset of the extracted features.

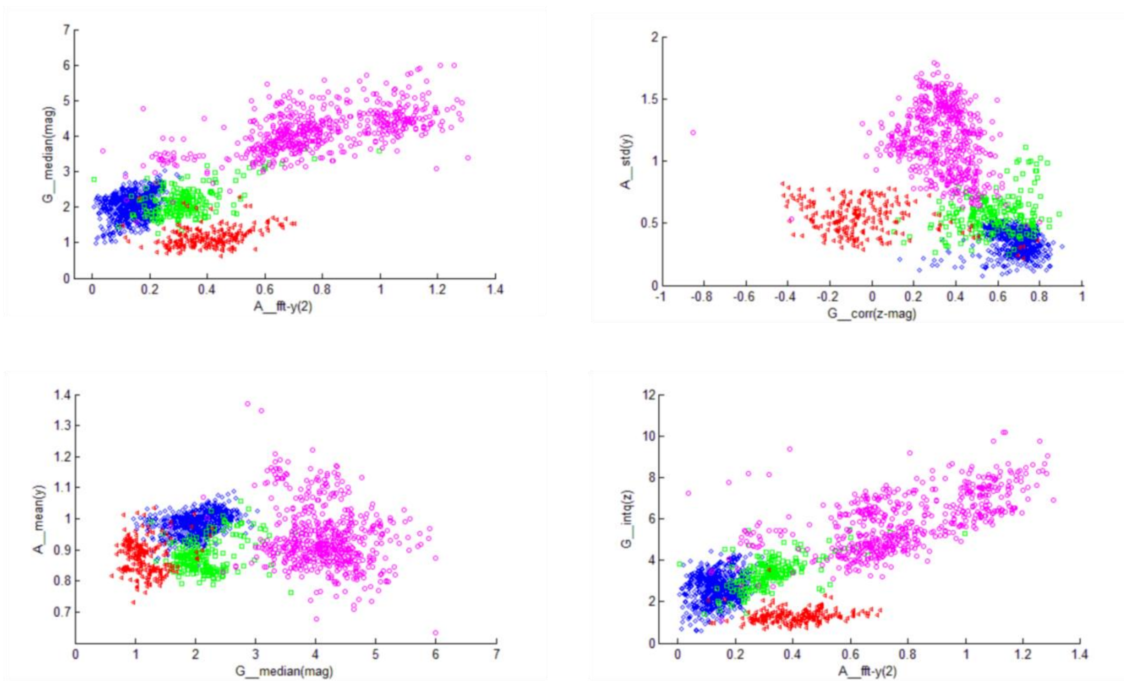

Figure 5-10 An example of activities clusters distribution over features selected by SVM, where pink, red, green and blue colors represents running, SA, SD and walking activities respectively.

5.4.3 Results and Discussion

5.4.3.1 Signal segmentation on pre-processing configurations

Signal segmentation is carried out on six different configurations of pre-processing to be tested:

1. Segmentation performed on raw signals (no further processing).
2. Segmentation performed on signals corrected for inclination (no further processing).
3. Segmentation performed on raw signal (then filtering applied on segmented windows).
4. Segmentation performed on signals corrected for inclination (then filtering applied on segmented windows).

5. Segmentation performed on filtered signals (no correction for inclination).
6. Segmentation performed on filtered signals (corrected for inclination).

The position of the inclination correction in the processing flow diagram does not have an effect on the segmentation quality, since the criteria based on absolute values for the angular velocity in the processing steps for segmentation are not affected by inclination correction.

Conversely, some earlier detections of foot-off events appeared on raw signals in some subjects, as compared to filtered signals. These differences are sometimes present in walking and stairs descend activities as shown in figure 5-11 (a) and (b) columns.

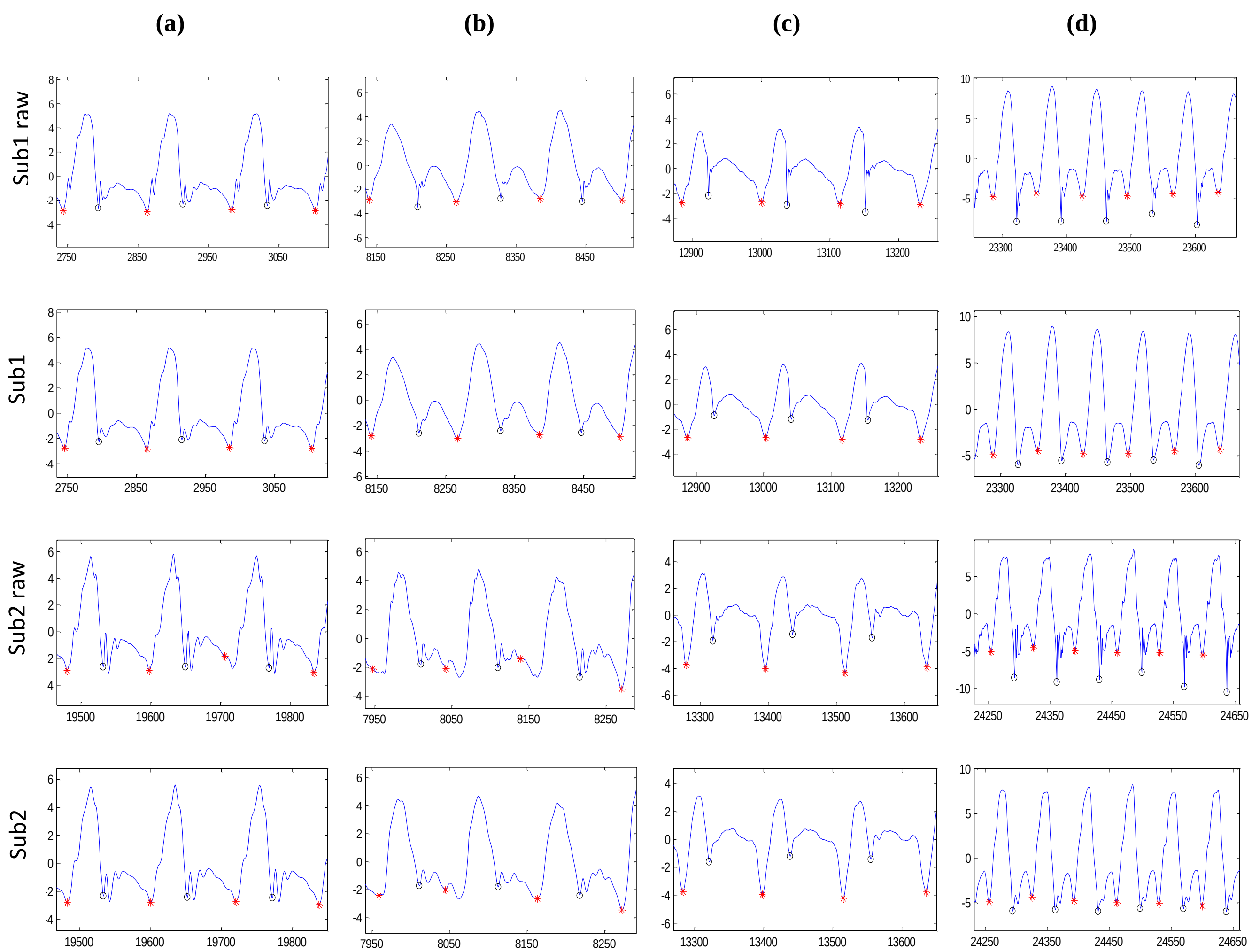

Figure 5-11 Signal segmentation based on gait events, zero circles are foot strike events and red asterisks are foot-off events; (a) walking; (b) stairs descending; (c) stairs ascending; (d) running.

Foot-off events are detected 40 ± 20 ms and 90 ± 40 ms before the actual events in walking and stairs descend activities respectively. Moreover, these early detections are mostly located between the heel-off (negative fall in signal) and toe-off (negative peak) points, so these windows also maintained the gait cycle information (swing and stance phase). In spite of these small differences, overall performance of the segmentation algorithm was quite good, as it detected 99.6% (2555 out of 2565) and 99.77% (2559 out of 2565) gait cycles from raw and filtered signals, respectively. Among them, 2 walking steps and 1 stairs ascents are not identified, 2 stairs descents and 2 stairs ascents are incorrectly identified (foot strike as foot-off) and there is no error in running activity identification.

5.4.3.2 Classification Results

Segments obtained from the six different pre-processing settings are fed to SVM to classify the ongoing activity. Leave-one-subject-out cross-validation criterion is used on the Biolab^2 dataset to evaluate the performance of the classifier. In the case of the Biolab^3 dataset, the classifier is trained on the overall data of the Biolab^2 dataset, and testing is performed on the Biolab^3. The final results represent the average accuracy over all subjects and specificity and sensitivity of each activity. Figure 5-12 illustrates the average classification accuracy on both datasets.

Classification performance of the event-based segmentation on the Biolab^3 dataset is pretty high (Average accuracy > 98% percent for all settings), with less variation among the pre-processing settings. In the Biolab^3 dataset, accuracy obtained with different settings has shown a higher (still not relevant) variation: as expected, average performance decreased for all the configurations. In both datasets, classification obtained with the raw signal resulted slightly higher than all the other configurations. Standard deviation (obtained by considering the different runs of the leave-one-subject-out approach) bars show that variation in performance among subjects performance rises when inclination is removed from the signal, as compared to the other configurations. To compare the results with previous studies, performance of each activity on raw data is shown in Table 5-8.

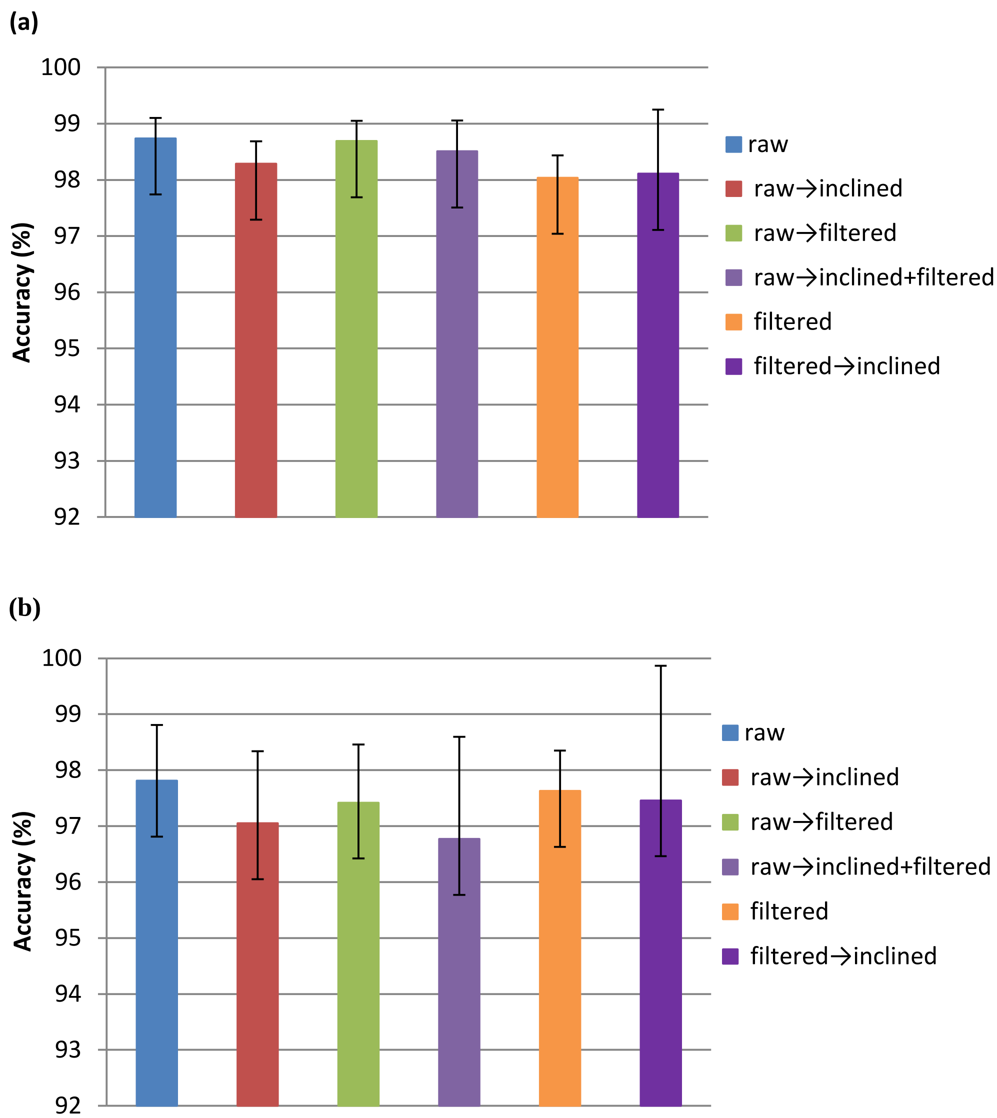

Figure 5-12 Average classification accuracy over; (a) Biolab2 dataset; (b) Biolab3 dataset.

The main idea of this study is the analysis of the gait inertial signal. There are number of studies confined to the signal segmentation and activity recognition but all of them are following the trend of the signal de-noising and window based segmentation. However these preprocessing steps may increase the system time and space complexity, when the problem is associated with the real time applications.

Table 5-8 Activities performance evaluation over raw data.

Activities	Confusion matrix				Performance measures (%)		
	WK	SD	SA	RUN	Specificity	Sensitivity	Step detection
WK	**99.3**	0.3	0.3	0.1	98.03	99.3	99.75 (1244/1247)
SD	3.4	**96.6**	0	0	98.53	96.6	98.9 (369/373)
SA	2.8	0	**97.2**	0	98.6	97.2	99.2 (372/376)
RUN	0.4	0.2	0.1	**99.3**	99.82	99.3	100 (570/570)

WK: walking, SD: stairs descending, SA: stairs ascending, RUN: running

5.4.4 Discussion and conclusion

5.4.4.1 The role of segmentation

The signal segmentation algorithm proposed in this study is based on heuristic rules and sequentially evaluates each sample. Also, it has been reported that a rule–based algorithm performed nine times faster than wavelets analysis based algorithms [63] [77], and this represents an advantage for real-time systems. Identification of the gait events is performed by considering timely detection, without using any window for backward or forward search for events. In the study, differences in the detection of the gait cycles from the raw gyroscope (z-axis) signal and from other pre-processing settings are not very significant, since all configurations reached an average detection accuracy > 99 percent, which is in accordance with other studies. For example,

Formento et al., [128] reported 95 percent event detection in stairs walking; Faracarro et al., [34] work achieved 92.5 *percent walking event detection; Catalfamo et al., [77] achieved 98 percent* gait event detection accuracy during ground walking and slope waking. In the mentioned studies, event detection was performed on the filtered signal and the window size of 80 ms to 250 ms was used to detect the foot-off event and additional 50 ms to 135 ms of event location difference was found.

5.4.4.2 The role of de-noising on classification

Foot-off events detected by the segmentation algorithm were taken as the reference point for the start and end of each activity cycle over which the features were extracted. Referring to the classification accuracy among pre-processing settings, performance obtained with the raw signal is consistent in both datasets, but not significantly different from other settings. In this study, feature set which is used to classify the activities is optimal; the information retrieved by these features was not affected by the presence or absence of the noise in the signal. Classification accuracy obtained from raw and filtered data is > 98%, which is higher than the previous studies where Chen et al. [31] achieved 94% accuracy, Panahandeh et al., [132] 95%, Coley et al., [32] 92.5% to classify between stairs ascent and other (walking and stairs descent), Ngo et al., [133] 94% and Chen et al., [33] reported 10.78 percent error with single stance, 3.42% error with double stance and 5.6% error with swing phase based recognition. All of these studies carried out classification on de-noised and event-based segmented data except Ngo et al. [133].

5.4.4.3 Final considerations

Different gait event detection algorithms have been used in the literature; rule-based segmentation [62] [77] [128], Hidden Markov Model [132], and wavelet analysis [32] [64]. All these studies validated their results on de-noised accelerometer/gyroscope signals and considered small windows for event detection. The performance of these algorithms show sufficient reliability from 92-99 percent to detect gait events but when it implies to the classification of the activities from those segmented events the highest achieved accuracy is 95 percent. While the segmentation detections achieved by the algorithm on raw gyroscope signal are in accordance with these studies and the classification results are higher (> 98 percent) than previous studies.

Our findings show that the pre-processing operators; inclination removal and signal de-noising has no significant impact on the segmentation and average classification of the physical activities. However there is a little difference in the earlier detection of the gait events among raw and filtered signals but the results show that this difference doesn't affect the classification performance. One might consider the use of raw inertial sensor data for the dynamic segmentation and classification of the daily locomotion activities from the shank mounted inertial sensor, as the use of noise removal steps has no significant effect on the segmentation and classification of the activities while it increases the complexity of the system for online applications: if the filtering used is composed of just 2 taps, at least 2*10 ms will be needed as waiting time, to have the preceding samples available for the processing.

5.5 Which feature selection technique provides best features for activity classification?

Studies presented in section 5.3 and 5.4 for activity recognition have been evaluated on the feature sets computed over two different feature selection techniques. A simple linear forward feature selection technique is used in one of the study to rank the most relevant features. Different combinations of the features are evaluated and based on the MLP classifier performance on all subjects and activities, 30 features produced best results. While in second study (section 5.4), SVM classifier based on ranker method is used to select the most relevant features and 20 features produced the best performance. Selected features from two different methods and their performance on classifiers are listed in Table 5-9 and Figure 5-13 respectively.

Table 5-9 Feature sets obtained from LFFS and SVM based feature selection technique.

	Selected features (LFFS)	**Selected features (SVM)**
Time domain		
Mean	a_x, a_y	a_x, a_y, a_{mag}
Median	a_y, g_z, g_{mag}	a_y, g_y, g_z
St. deviation	a_x, a_y	a_x, a_y, g_z
Skewness	a_z	a_z, g_z
Correlation	$g_{z,mag}$	$a_{x,z}$, $a_{x,mag}$, $g_{x,mag}$, $g_{y,mag}$, $g_{z,mag}$
Interquartile range	g_z	
Frequency domain		
Mean		a_{mag}
St. deviation		A_x, a_y, g_{mag}
Skewness	g_z	g_x
Kurtosis		g_z
Energy	a_x	a_x
1st five FFT components	$a_x(2)$, $a_y(1,2,3,5)$, $a_{mag}(1,2)$, $g_z(3)$	$a_x(2)$, $a_y(2,5)$, $g_y(4)$, $g_z(1,2,4)$

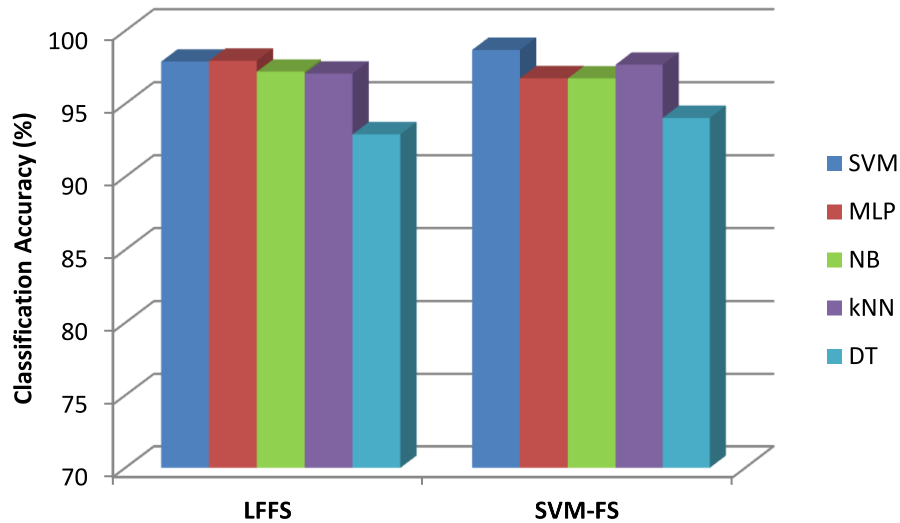

Figure 5-13 Recognition accuracy using different number of features over different classification schemes.

Classification results shown in above figure are obtained on the subject independent validation. As it can be inferred from Figure 5-14, SVM-FS has the best recognition accuracy over the classification schemes. Table 5-10 lists the amount of time required to train the classifiers over the 35 minutes of data.

Table 5-10 Comparison of time required to train the classifier over different feature sets.

	Time (s)	
Classifiers	**LFFS**	**SVM_FS**
SVM	0.21	0.7
MLP	6.41	37
NB	0.08	0.18
kNN	0.01	0.09
DT	0.1	0.48

Model learning time increases three times in most of the classifiers with the larger feature set. Although SVM classifier requires more computational time as compared to NB and kNN, it produces less recognition variation among the subjects and activities as validated by Cohen's Kappa statistics in section 5.2. It is thus recommended to use SVM-based feature selection technique to get those features which show high discrimination among the classes but less among the subjects. Additionally, the features obtained from SVM-FS produce the highest accuracy among classifiers as well.

6

Conclusion

The aim of this thesis was to design a physical activity recognition system intended to classify motor activities from inertial sensors, which can be profitably used in real-time applications. The study was motivated by the fact that it is important to monitor the activities of a person in daily routines, so as to associate the performance with the recommendations given by the physicians. A set of aerobic activities which are considered useful to promote the well-being of a person were used to design the activity recognition system. To achieve this goal, the system was designed and evaluated by considering the following four main steps: 1) pre-processing steps involved in signal processing, 2) segmentation of the signal to minimize delays associated with further processing, 3) determination of the best feature set for classification, and 4) training of the classification scheme based on both subject-dependent and subject-independent validation to maximize recognition accuracy. All these issues were addressed in the studies drawn in sections 5.2, 5.3 and 5.4.

Activity recognition algorithms presented in this thesis are based on two different sensor set-ups: 1) classification of daily living physical activities including sitting, standing, walking, stairs ascending, stairs descending and transitions between the activities, using a waist-worn accelerometer – study 1; 2) identification of gait events and their classification as walking, stairs ascending, stairs descending and running through a shank-located inertial sensor – studies 2 and 3.

This section draws the conclusion on the results obtained in these studies.

Study 1 Sliding window based segmentation on the classification of daily living activities including transition activities

- inclusion of short and long duration activities
- using different window sizes, classifiers
- training and testing data requirements

Study 2 Activity classification based on event-based dynamic segmentation

- development of real-time dynamic segmentation algorithm
- comparison among window based and dynamic segmentation
- validating algorithm on benchmark dataset

Study 3 Preprocessing effect on the activity identification and classification

- investigating de-noising and inclination removal preprocessing steps on segmentation and classification
- evaluating feature selection technique

Figure 6-1 Evaluation chapter overview.

6.1 Conclusion

Conclusions on study 1

This study contributes to define the following elements: 1) choice of the best window length to be used for segmentation on both short and long duration activities, 2) amount of training data required to build the classification model, 3) evaluation on different classifiers performance.

Experiments demonstrate that the use of 1.5 s (and in some cases, 1 s) window can accurately classify static, dynamic, and transitions activities, considering both short and long duration ones. Shorter window sizes might be helpful in classifying between static and dynamic activities, but fail if it is required to distinguish among dynamic activities: in effect, this temporal support does not sufficiently capture data differences coming from the varying behavior of the dynamic activities. Longer window sizes respond well on long duration dynamic activities, but this is counteracted by an increased misclassification rate for short duration activities. Also, larger window sizes provide decreased accuracy when dealing with transitions, and the delay in real-time human activity recognition may be relevant.

Evaluating the training data splits and classifiers, in subject dependent validation different percentage splits for training data were analyzed and found that 50% and 70% of the training data achieved an overall accuracy of the 90.87 % and 91.15 % on 1.5 s window respectively. Most classifiers reached their peak accuracy with either 1 or 1.5 s window size, with 1.5 s appearing most often. With these window sizes, in subject-dependent validation, the highest accuracy was achieved by SVM (accuracies > 90%) followed by MLP and NB, with accuracies just a few percentage points lower. In subject-independent validation, the performance of classifiers varied from subject to subject, with the average performance of SVM being high (values > 87.5%) and better than the other classifiers (both for 1 s and 1.5 s), with kNN and MLP respectively following.

Conclusion on Study 2

This study was designed to contribute to the limitation of the static window-based segmentation approach, a problem that often arises if an activity lasts significantly shorter or longer than the pre-defined window length, or when a person shifts from one locomotion activity to other (shifts among walking, stairs walking, running). This study contributes to designing and implementing a segmentation algorithm which can accurately segment the locomotor activities based on the gait-events detection. The proposed algorithm was also investigated on the benchmark dataset PAMAP2. A comparison between dynamic segmentation and static segmentation was also presented in terms of classification accuracy.

As an improvement to previous studies, a modification to a standard gait segmentation criterion was done in such a way that no explicit window segmentation was used to detect the events of the locomotor activities from raw gyroscope data. Based on the segmentation algorithm performance, it was found that event-based dynamic segmentation technique correctly identifies almost all the activity events (> 99% in both datasets), with misidentification of only 5 activity cycles (out of 1752): among them, one walking and one stairs ascent cycle was not identified because of lower mid-swing peak; in one walking, stairs ascent and stairs descent cycle, foot-off were not identified. All the running activity cycles were correctly identified. Foot-off events were identified 40 ± 20 ms and 90 ± 40 ms before the actual events in walking and stairs descend activities respectively.

For comparison with static segmentation, different lengths of the static windows were selected based on the average time duration of the gait cycle, which were 1 s, 1.25 s and 1.5 s. In regards to the datasets, classification accuracy was shown to depend on the feature set. However, performance of the neural network on the proposed event-based dynamic segmentation was around 97 % on both datasets and was significantly higher than that obtained with the relevant fixed size windows, <90 % for 1s and 1.25 s windows and 92% for 1.5 s window.

Conclusion on Study 3

The proposed event-based dynamic segmentation algorithm was implemented on the raw gyroscope signal, whereas literature arguments that preprocessing of the signal is necessary to identify and classify the gait events. Thus based on this argument, this study investigated the impact of preprocessing parameters (inclination removal and noise filtering) and six different configurations of pre-processing were carried out: segmentation performed on raw signals (no further processing); segmentation performed on signals corrected for inclination (no further processing); segmentation performed on raw signal (then filtering applied on segmented windows); segmentation performed on signals corrected for inclination (then filtering applied on segmented windows); segmentation performed on filtered signals (no correction for inclination); segmentation performed on filtered signals (corrected for inclination).

It was found that, comparing the events identification among raw and preprocessed signal, inclination removal has no significant effect on the identifications. While some earlier detections of foot-off events that appeared on raw signal in some subjects (walking 40 ± 20 ms and stairs descending 90 ± 40 ms) are compensated in filtered signals in some cases). In spite of these small differences, overall performance of the segmentation algorithm was quite good, as it detected 99.6% (2555 out of 2565) and 99.77% (2559 out of 2565) gait cycles from raw and filtered signals, respectively.

Classification performance was evaluated on the feature sets obtained from two feature selection methods: LFFS (30 features) and SVM-FS (20 features), and it was found that time taken by the classifiers to build a learning model was 3 times greater on LFFS feature set as compared to SVM_FS. Also the higher accuracy was achieved on the SVM-FS feature set with accuracy of 98.69%.

Considering the classification results on two datasets, in Biolab2 dataset classification accuracy higher than 98% was achieved on all settings. Whereas in Biolab3 most of the settings produced accuracy higher than 97%. Still, in both datasets Biolab[2] and Biolab[3], classification obtained with the raw signal resulted slightly higher than all the other configurations, with accuracy.

Findings show that the pre-processing operators; inclination removal and signal de-noising has no significant impact on the segmentation and average classification of the physical activities. However there is a little difference in the earlier detection of the gait events among raw and filtered signals but the results show that this difference doesn't affect the classification performance. One might consider the use of raw inertial sensor data for the dynamic segmentation and classification of the daily locomotion activities from the shank mounted inertial sensor, as if the filtering used is composed of just 2 taps, at least 2*10 ms will be needed as waiting time, to have the preceding samples available for the processing.

6.2 Research contributions

With reference to the challenges faced in activity recognition systems addressed in the previous chapters, this section summarizes the contributions of this thesis addressing some of the challenges generally associated with the recognition of motor activities from inertial sensors.

- The recognition of aerobic activities from a single inertial sensor which can help to verify one person's ability to conform to the recommendations regarding physical activity.

- The location of the sensors in the investigated datasets was chosen in such a way that they can be easily integrated into mobile phones placed at the waist level, or into instrumented anklets.
- To capture the variability in movement patterns during data collection, subjects were asked to perform activities by his/her own manner.
- Different preprocessing measures were evaluated in terms of identification and classification of the activities.
- The effect of window length segmentation was evaluated in terms of identification of the short and long duration activities.
- Preprocessing was found to having no significant effect on the accuracy in gait-event identification and classification of activities.
- Different feature selection techniques and classification schemes were compared with respect to their processing time.
- A modified event-based segmentation algorithm was presented that introduces a very less delay between activity occurrence and detection.
- The presented segmentation algorithm was not only capable to classify activities but can also be helpful in clinical gait analysis where on-time processing is concerned.
- Accuracy of the recognition system was assessed on subject-independent validation.

6.3 Future research directions

Some research directions for future are outlined here, as possible improvements to the work done in this Ph.D. thesis.

- Create some more data from other age groups and clinical pathologies.
- Addition of other home and sports activity and different intensities.
- Modification and adaptation of segmentation algorithm when new classes are introduced in the data.

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APPENDIX A) ACTIVITY RECOGNITION LITERATURE

Literature on Study 1

Table A.1 Summary of past work on the activity recognition based on fixed window length segmentation

Study	No. of Sensors	Activities	Segmentation / Filtered	Data generalization	Data validation / Classifiers	Classification accuracy
Mantyjarvi et al. (2001) [134]	2 acc	SA, SD, WK	Fixed size (2 s)		Cross validation / MLP	83-90%
Bao and Iintille (2004) [13]	5	20 including ambulation and home activities	6.7s (50% overlap) / n.a.		Subject dependent and independent / DT, NB	84.26 %
Ravi, et al., (2005) [81]	1 acc	8 ambulation, Brushing teeth , Vacuuming	5.12s (50% overlap) / raw	10s discarded from start and end of activity	Subject dependent	83%-90%
Maurer et al. (2006) [76]	6 acc	RUN, SA, SD, Sit, Std, WK	4s			87%
Wang et al., (2007) [135]	1 acc	WK, SD, SA	2.56(50% overlap) / raw		70%-30% split, subject independent / wavelet decomposition & MLP	92.5%, 88.54 %
Preece et al., (2009) [22]	1 acc	WK, SD, SA, RUN, Jog, Hopping, Jumping	2s (50% overlap) / raw	Excluding windows with transitions	Subject independent / k-NN	95%
Hong et al., (2010) [15]	3 acc, 1 RFID	18 including Ambulation and instrumented activities	4s (50% overlap) / n.a.		Subject independent / DT	95%

Khan et al., (2010) [17]	1 acc	WK, SA, SD, RUN, Sit, Std, Laying, transitions	3.2 s (no overlap) / filtered		Subject independent / hierarchical model	97.6%
Lee et al., (2011) [26]	1 acc	WK, SA, SD, Std, Laying, Driving	10s (50% overlap)		Subject dependent and independent / state classification using NN	94.43 %, 96.61 %
Godfrey et al., (2011) [136]	1 IMU	Sit, Std, WK, postural Transitions	n.a.		N.A / Rule based	86%-92%
Ugulino et al., (2012) [137]	4 acc	Sit, Std, Sitting down, Std Up, WK	1s (150ms overlap) / n.a.		10- fold validation / DT	
Wang et al. (2012) [129]	1 smartphone	WK, Jog, SA, SD	Fixed size (0.5 s, 0.8 s)			93.3%
Banos et al., (2012) [16]	5 acc	WK, Sit, Std, Relax, RUN	6.7s (50% overlap) / filtered		10-fold validation / SVM, DT, NB	>95%
Dalton et al., (2013) [11]	5 acc	WK, SA, SD, RUN, Sit, Std, Laying, Transitions, Household	0.25s, 0.5s, 1s, 2s, 4s / filtered	15s discarded from start and end of activity	Subject dependent and independent	90%
Cleland et al., (2013) [12]	6 acc	WK, SA, SD, RUN, Sit, Std, Laying	10s (50% overlap) / raw		Subject dependent	97%
Chan et al., (2013) [21]	1 IMU	SD, SA	n.a. / filtered		10-fold validation / MLP	95.7%
Bayat et al., (2014) [30]	1 acc	WK, SD, SA, RUN, Dancing	1.28s (50% overlap) / filtered		10-fold validation / SVM, MLP	91.15 %
Deng et al., (2014) [138]	1 acc	WK, SA, SD, Std, Sit, Laying	2.56s (50% overlap) / filtered		80%-20% split / SVM	>90%

Shoaib et al., (2014) [25]	5 IMU	WK, SA, SD, RUN, Sit, Std, Jog, BK	2s (50% overlap)		10-fold validation / SVM, MLP, K-NN, DT	>90%

Abbreviations: IMU(Accelerometers and Gyroscopes), acc (Accelerometer), gyro (Gyroscope), Jog (Jogging), BK (Biking) RUN (Running), SA (Stair Ascending), SD (Stair Descending), Sit (Sitting), Std (Standing), SW (Slope Walking), WK (Level Walking), DT (Decision tree), NB (Naïve bayes), SVM (Support vector machine), MLP (Multilayer perceptron), k-NN (k-Nearest neighbor), NN (Neural network).

Literature on Study 2 & 3

Table A.2 Summary of past work on the event-based activity identification and classification

Study/Sensors	Sensors	Activities	Segmentation/filtering	Classification accuracy / gait event detection
Lau et al. (2008) [85]	2 IMUs	WK, SA, SD, SW	Event-based / filtered	85-100% / n.a.
Chen et al. (2009) [31]	1 IMU	WK, SA, SD	Peak to peak event detection / filtered	92-95% / n.a.
Catalfamo et al., (2010) [77]	1 gyro	Level WK, SW	Rule based event detection (120ms delay) / filtered	n.a. / 98%
Lee & Park (2011) [139]	1 gyro	Slow, normal, fast WK	Rule based event detection (320ms delay) / filtered	n.a. / 100%
Mannini & Sabatini (2012) [140]	1 IMU	WK, Jog	HMM based event detection / filtered	94% - 98%
Barth et al., (2013) [141]	1 IMU	WK, SD, SA	DTW based event detection /	n.a. / 86.7%-97.7%
Panahandeh et al. (2013) [132]	1 IMU	RUN, SA, SD, Std, WK	HMM based event detection / filtered	95% / n.a.
Fraccaro et al. (2014) [34]	1 acc, 1 gyro	WK	Rule based event detection / filtered	n.a. / 92.5%
Formento et al. (2014) [128]	1 gyro	SA, SD	Rule based event detection (120ms delay) /filtered	n.a./93-95%
Ngo et al. (2015) [133]	3 IMUs	WK, SA, SD, SW	Signal matching based event detection /filtered	94%
Chen et al. (2015) [33]	2 IMUs and foot pressure	WK, SA, SD, SW	Event-based /raw	n.a./90-100%

Abbreviations: IMU(Accelerometers and Gyroscopes), acc (Accelerometer), gyro (Gyroscope), Jog (Jogging), SA (Stair Ascending), SD (Stair Descending), Std (Standing), SW (Slope Walking), WK (Level Walking),

APPENDIX B) KINEMATIC DATA ACQUISITION

Kinematic Data Viewer App

Kinematic data viewer App was developed in Java using the NetBeans Software Development Environment 7.0.1. This App allows the direct connection between the inertial sensor and the laptop system over a Bluetooth connection.

Connecting device

Running the app, a graphical panel opens which facilitates to select and connect the device(s) with the laptop, shown in Figure B.1.

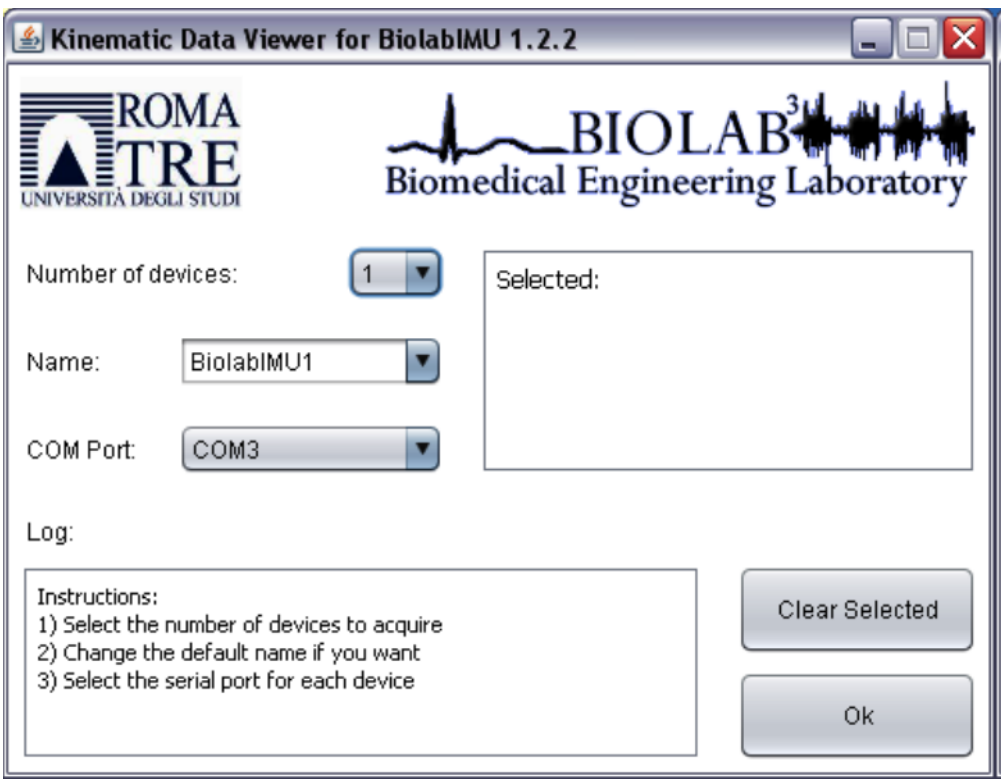

Figure B.1 Main (Kinematic Data Viewer) window for connecting BiolabIMU.

In this window a user can choose the number of devices to acquire the data, name given to each of them and the COM port that has been associated with the pairing between the IMU and laptop over Bluetooth connection:

Number of devices: Select the number of devices to be scanned, up to four inertial units.

Name: Select the name for the device. This will be the only reference to later identify the inertial unit in the graphics and text files.

COM Port: Select the port associated with the device. Note that once selected is removed from the list.

Selected: Here is a list of the devices to be scanned with the respective associated COM ports.

Log: Here user can view the operations performed by the software, and all messages displayed for the user, including error identified from the header Warning!

Clear Selected: Deletes the selected list and restores the window to its initial state.

OK: The software opens the chosen ports and connects them; verification that each associated device responds to a reading start request; synchronizes all connected devices to obtain simultaneous data acquisition necessary for proper display in graphics.

Data acquisition and viewing

Once all devices are successfully connected, a new graphical window will appear. This window allows to acquiring and viewing the incoming data. Buttons on the bottom of the window are to controlling the device; calibration, get the data, pause and stop. The panel on the right side is to manage the charts of the devices; which device to display by selecting the name assigned by the user. Upper panel is for displaying accelerometer and gyroscope signal, "All in one" shows all axes of accelerometer and gyroscope in separate graphs, "Acc + Gyro" displays two graphs, one containing three axes of the accelerometer and one containing all three axes of the gyroscope. And finally "Custom", it displays a single chart and has different controls than those of previous panels. User can choose any channel of any device and add it to the chart. Figure B.2 shows the screenshot of the panel, showing incoming signals from two inertial sensors.

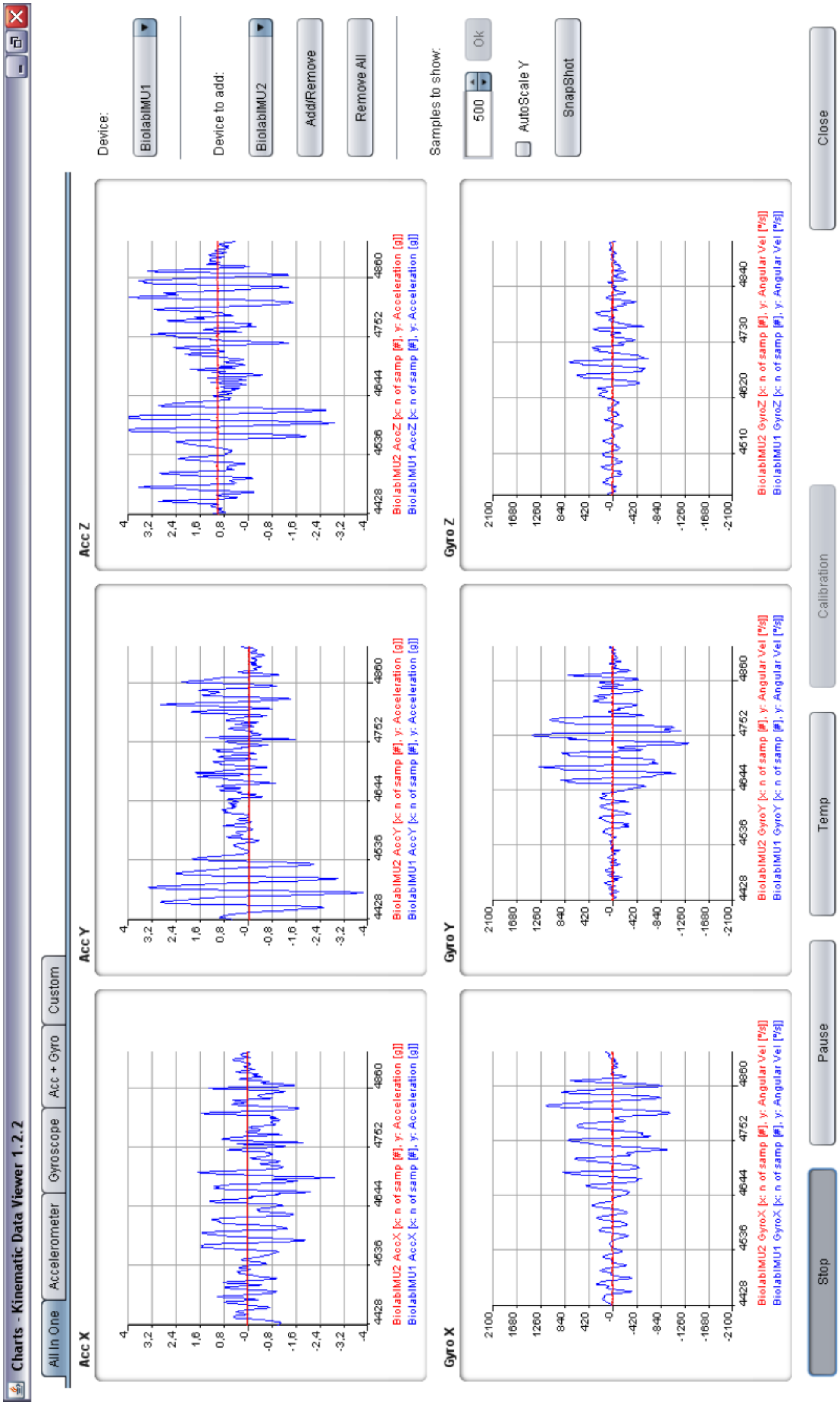

Figure B.2 Data acquisition and viewing Panel