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Data Analysis for Physical Activity Monitoring

Master's Thesis in Computer Science
by

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‘Never trust anything that can think for itself if you can’t see where it keeps its brain.”

J.K. Rowling

Abstract

Physical activity is essential for humans for maintaining a healthy and comfortable lifestyle. With science and technological advancements, there comes various guidelines for the amount of physical activity a person should perform. Monitoring the physical activity enables us to follow those guidelines and be aware of own activity.

Wearable computing is allowing us to track and monitor our own performed physical activities by mostly intrinsic (minimal) interaction.

Physical activity monitoring is an emerging research area in wearable computing. Our thesis is about identifying and classifying which activity is being performed.

We have used various classifiers and evaluation metrics to validate our classifier models.

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Abbreviations

HAR	**H**uman **A**ctivity **R**ecognition
ADL	**A**ctivities (of) **D**aily **L**iving
IADL	**I**nstrumental **A**ctivities (of) **D**aily **L**iving
ubicomp	**Ubi**quitious **Comp**uting

Chapter 1

Introduction

Technology... the knack of so arranging the world
that we don't have to experience it.
— Max Frisch

"The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it." [1]

Mark Weiser in 1998 coined the term *ubiquitous computing*. He had a theory that computers in the future were going to become so pervasive in our lives that they will work non-intrusively in the background, to improve human experience and quality of life. Fast forward to today and his vision is well on its way to becoming reality. From computers in our bags and pockets to rooms, buildings and cities, they are truly well integrated and out of sight that we don't even think about it. Smart phones and watches, home automation systems, self-driving cars, various sensors embedded in everything - they are practically *everyware* (another name for ubiquitous or pervasive computing).

An important part of the pervasive computing is that it works in background without being intrusive. That is possible by making the interaction with the computers implicit rather than explicit - meaning that a user doesn't have to explicitly turn a switch on, it should detect the action of the user and perform the required task by itself. Sensors are a great resource for that - sensing the context of the user interaction and triggering action. Interpreting the user's action correctly depending on his environment is what *context-aware computing* is all about. Context aware computing is a intrinsic part of the ubiquitous computing. By being aware of the surrounding and anticipating the user's need and performing that task seamlessly and proactively is what will make computers disappear.

"In essence, that only when things disappear in this way are we freed to use them without thinking." [1]

Wearable computers and gadgets are making it possible for a common person to monitor his own physical activity, which was not possible in recent past. Monitoring physical activity is an emerging interesting field attracting new research.

Our thesis is about analyzing the data we get from these wearables and detecting the actions being performed by the user by the help of machine learning. In the next section we will explore the motivation for monitoring an individual's physical activity and the potential for future applications. Next we also delve into the challenges faced in activity recognition.

1.1 Motivation

According to study, most of the world's population live in countries where overweight and obesity kills more people than underweight. [2] But according to the same study, it is preventable with the help of balanced diet and regular physical activity (60 minutes a day for children and 150 minutes spread through the week for adults).

There are numerous benefits of engaging in regular physical activity; some of them according to [3, 4] are:

- It strengthens the heart and reduces your risk of a heart attack by helping keep arteries and veins clear.
- It strengthens the lungs.
- It controls and helps manage your weight better.
- It reduces blood sugar levels and lower the risk of type 2 diabetes and some cancers.

- It strengthens bones, muscles and joints and lower risk of developing osteoporosis.
- It regulates blood pressure.
- It lower your risk of falls.
- It helps you recover better from periods of hospitalization or bed rest.
- It helps you feel better - with more energy, a better mood, feel more relaxed and sleep better.

According to a NIH (National Institute of Health) study, even low level leisure time physical activity can increase the life expectancy as much as 4.5 healthy years. [5] Supporting this, another study states that small bouts of activity can increase lifespan in older men. [6]

Physical activity has also proven to be a great help with people dealing with depression and anxiety. It releases endorphins that enhances the good mood. It also helps with the sleep problems, for mood boosting, energy levels, confidence and all round feeling good. [7]

From the above mentioned examples we can see that physical activity is crucial in human lifestyle. Now comes the need to monitor the level of physical activity a person is performing in order to measure if it meets the recommended requirements for health, or, in case of other fields, correctly recognizing the activity to log into the system.

Besides the health field we also use activity recognition and monitoring in various other fields of businesses. In entertainment industry - from games to mobile applications, in sports field and various other industrial sectors physical activity monitoring has a huge scope. We will further expand on these applications in Chapter 2.

In our thesis, this is our focus: to correctly recognize the physical activity being performed by the user. Wearable computing has made it possible to realize this goal.

1.2 Challenges

Physical activity monitoring is a realizable goal and it is being met by various up and coming researches and applications, but it has its limitations on data acquisition and accuracy. There are many challenges that researches face in activity recognition. We will discuss a few of them below:

Privacy and Data Security With ubicomp applications everywhere and expanding and collecting data - the people are rightfully conscious of privacy and data security issues. It has already being manipulated in these times by hacking of cloud networks being so common, that users are rightfully worried. It is important that applications which are collecting data have the user's consent and a heavy encryption and data security features.

Unsupervised Learning Most of the work done in activity recognition field depends on supervised learning from datasets complete with annotations. But obtaining such a dataset is not easy. Due to this the datasets available are based on data collected from a few individuals and not many activities which does not help with reliable estimation.

We have a lot of data being collected from ubicomp devices, which is not completely annotated, which can be useful if unsupervised or semi-supervised learning methods took hold in activity recognition field. A study [8] shows that the interest in semi supervised learning is gaining more popularity as a solution method.

High-Level Activities High level activities are accumulation of many low-level activities. Chapter 2 discusses this in detail. Most of the work done in activity recognition area is on the recognition of low-level activities. High-level or long time activities still pose challenge to the researchers in the sense of defining them and modeling learning algorithms.

Hardware Sensors are a great and vital resource for activity recognition, but they have limitations in respect to their size and battery life. As they are becoming smaller and less intrusive, they cannot hold a very large battery power. Thus, compromise must be made between high accuracy and performance and less power or less accuracy and more power.

It also is a challenge that one sensor cannot be dedicated to recognizing a multitude of activities performed by a person. There are inertial sensors for the physical activities, psychological sensors for other activities, heart rate sensor for detecting the effort and intensity, etc.

1.3 Contributions

- This thesis focuses on the various methods used for recognition of physical activity recognition and deciding which of them are better and what conclusions they reach.
- We will use multiple metrics to evaluate our models.
- Three different methodologies are used for validation purposes. We will also look at the research gap which needs to be filled and the future work that needs to be done.

1.4 Used Software

Following are the open source software used in this thesis:

Software For Writing Thesis Report

- Overleaf: online LaTeX editor
- Notepad++

Programming Language and Tools

- Python 3.6
- Anaconda Jupyter Notebook
- JetBrains PyCharm IDE

Libraries used

- Pandas

- Scikit-learn
- Numpy
- Matplotlib

1.5 Thesis Outline

This thesis is structured in the following manner:

Chapter 1 defines the field of ubiquitous computing and its sub-branch of physical activity recognition. We emphasize on the need for physical activity in daily life of humans and the importance of monitoring the physical activity for use in different fields.

Chapter 2 discusses the related work done in other studies and by researchers and we look at the various methods used by them.

Chapter 3 will introduce the dataset being used for our study: the PAMAP2 dataset. It is a open-source dataset with reasonable participants. We will explore the dataset in its properties in this chapter. We will also look at the pre-processing of the given data.

Chapter 4 will focus on the data processing chain and feature extraction and analysis. Here, we present the experimental work done by us on different classifiers and machine learning techniques.

Chapter 5 provides details about the evaluation process and presents the results of the study and discusses them.

Chapter 6 will present a conclusion and discuss the future work that needs to be done to fulfill the gaps that are present today.

Chapter 2

Related Work

If it keeps up, man will atrophy all his limbs
but the push-button finger.
— *Frank Lloyd Wright*

Human activity recognition (HAR) is an up and coming field of science being studied diligently for its uses in various fields like health, physical therapy, sports, fitness coaching, elderly assistance, homecare systems, prisoner monitoring, security, and so much more. The goal of activity monitoring is to recognize the activity being performed and the intensity with which it is performed with. With the advancement in hardware technology, especially in wearable computers, it is being made possible to do so with increasing accuracy. With so many applications of the topic the interest and research has leaped over the years. For example Figure 2.1 shows the interest in the topic 'activity tracker' has increased with time.

Figure 2.1: Interest over time on topic 'Activity tracker' [2004 - present] [9]

There used be a time when computers could not be 'worn'. It was in the 1990's that wearable computing was made possible. And with it opened a whole world of possibilities, research and inventions.

2.1 Applications

In this section we explore different areas of application for the wearable computing and activity recognition. There are a lot of applications of activity recognition. Its not possible to mention all. We will mention a few below.

Healthcare and Lifestyle Ranging from elderly assisted living to daily monitoring of vital signs, the uses of activity recognition in the field of healthcare are immense. From 1980's it has been the focus of medical community to recognize the human physical activity for the purpose of measuring oxygen consumption or energy expended [10] [11].

In the 1700's life expectancy was much lower and need for assisted living was not a necessity. But with time life expectancy is increasing and fertility rate is declining - i.e. more older population, which sets a need for the elderly assisted living. Activity recognition can help with that by:

- recognizing major impacts such as fall detection [12–16],
- monitoring daily activities to prevent health problems,
- sleep monitoring by detecting sleep patterns, time a person sleeps, etc. [17–19]
- providing useful data to doctors and practitioners to diagnose or evaluate the progress of a patient.

Besides the above mentioned points HAR also helps with rehabilitation of patients [20–22], assist people with disabilities [23–25], motivate people to meet their workout or calorie burning goal with reminders, alarms and customized workouts.

Also, as mentioned in Section 1.1 there are multiple other areas of healthcare that physical activity monitoring can help with.

Sports and Fitness Starting from basic pedometers to today's advanced Fitbit systems [26] and smart watches, activity recognition has come a long way in the field of sports and fitness. There is a huge array of applications and wearables available in the market today which is focused mainly on measuring and monitoring the individuals' activities and provide feedback and motivation. These applications provide individual details about the activity performed like distance travelled, duration and intensity, calories burned, etc. Work has also been done in recognizing the sport activities. Recognizing the activity pattern, maximum speed, performance analysis, etc.

Gaming Research in gaming industry on motion sensing controllers and VR systems has sparked interest in consumers for more. It gained popularity with Nintendo Wii [27] in 2006 and has evolved to today's full boy virtual reality systems like Oculus Quest [28]. Since there is no pressure on 100 percent accuracy as opposed to the healthcare field, more consumers and developers are investing into it. In fact, some research has also suggested that playing interactive physical games on these gaming consoles - like Nintendo Wii - may lead to better physical therapy and a healthy elderly population [29].

Industrial and Other Physical activity monitoring can help in industrial applications such as helping workers with safety, analysis of daily tasks, support and training. Wearable technology helps the workers in looking up or gathering data, communication and tracking coworkers. It also is of use in workshop or assembly activities in industries, such as, in car or plane manufacturing. Companies can utilize this by tracking the workers' progress and gain feedback, get warnings and notifications about the work [30].

There is also work done for assisting hospital field by delivering patient notes on mobile devices to relevant staff, displaying priority patients, maintaining their health status automatically [31, 32]

Besides the above mentioned applications, there are various other fields where activity recognition systems are in effect and numerous new areas where research is being done. Some of the work done is in the following fields:

- Use of activity recognition for target or context-aware advertising [33].

- Uses in military by tracking soldiers [34]
- Robotics field also uses activity recognition to interact with objects and people
- Surveillance applications
- In educational field, [35] explores learning a new language with the help of RFID tags.

2.2 Activities

Huynh [36] describes the activities performed by an individual in three categories: gestures, low-level activities and high-level activities.

Gestures are movements performed in seconds like a wave or bending an arm. These very short timed activities might prove to be harder to recognize as they might be done as a specific gesture or it might just be a random movement, and isolating them from background data could also be challenging.

Low-level activities are performed in scale of minutes; like walking, talking, running, eating, etc.

There is a lot of work done on monitoring and recognizing low-level activities. It is possible to recognize these type of activities by just one tri-axial accelerometer [37]. [38–41] also focus on data acquired from single sensor. Smartphones have opened a new dimension of study in recognition of activities based on sensors in the mobile phone only. This has its own challenges also. Work done by [42–44] using mobile phone for activity recognition has brought forth problems and solutions for energy consumption, position and orientation and training, etc.

We will focus mainly on the low-level activities in our paper, as the dataset we are working with consists mainly of low-level activities as shown in Table 3.1.

High-level activities are done over a period of hours and are a collection of low-level activities. These activities can include getting ready, working at office, shopping, sightseeing, etc. Recognition of high-level activities depends on recognizing the low-level activities and the order in which we perform them. We can establish a pattern from low-level activities for the detection of the high-level activities. [45] There has been some work done in classifying high-level activities, but with limitations. Recognition of high-level and long time activities still needs work.

Activities of Daily Living On the other hand, activities of daily living (ADL) cannot be simply placed by these three categories. ADL were first described by [46] for the field of healthcare in determining the activities a person should perform to stay healthy. List of ADL activities, since then, have been improvised and added on. ADL activities include: personal hygiene(bathing, grooming, etc.), use of bathroom facilities, dressing and feeding oneself.

In addition to ADL activities there are Instrumental Activities of Daily living(IADL) which comprise of activities which prove that a person can live independently like grocery shopping, preparing meals, socialization and companionship, etc. Recognition of ADL in conjunction with IADL is a great focus in healthcare field.

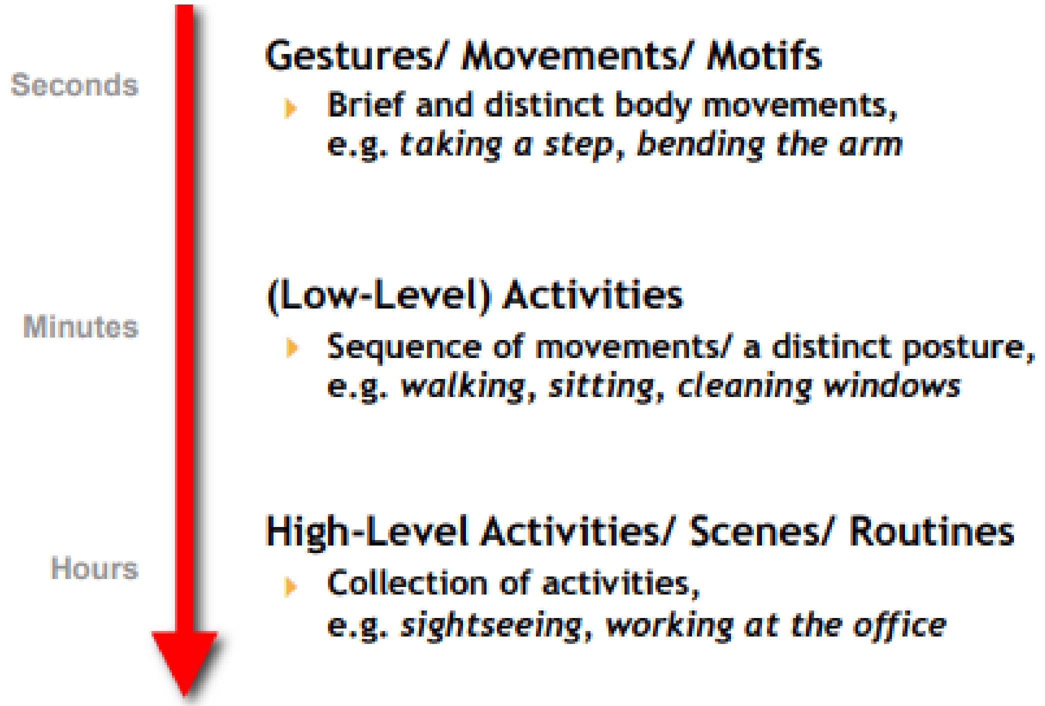

Figure 2.2: Activities categorized base on duration. Source [36]

2.3 Sensors

Sensors for activity recognition range from fairly simple to complex and small to large scale. There are sensors with discrete signals(switches, RFID tag readers) and sensors with continuous signals(accelerometers). More complex sensors include audio and video signal processing.

Some common sensors used are discussed below

Inertial Sensors Inertial measurement units(IMUs) are fairly good sensors to work on activity recognition. It has been studied that recognition of a number of activities is done, with only IMUs placed on human body, with high accuracy.

Early work in activity recognition was done on accelerometers [11] [10]. Accelerometers are a popular sensor in activity recognition as they are small, accurate, cheap and non-intrusive (as opposed to camera and microphone).

Physiological Sensors Physiological sensors, such as heart rate monitor and temperature, also provide a good source of information for activity recognition. But it comes with its own set of challenges - more expensive, slow response(for example heart rate stays elevated even after stopped running), intrusive and, according to some studies [41], does not correctly recognize the activity on physiological data alone. Whereas, when used in conjunction with inertial sensors, they can measure the intensity of the work done (how fast/hard run, carrying heavy or light weight, etc).

But according study done by [47] physiological sensors are useful in distinguishing and differentiating between some activities.

Image and Audio based Sensing Images, videos and audio are also being used for the monitoring the activities of the people. Images and audios provide good data for analysis but they are also harder to analyze, and the sensors (i.e. cameras and microphones) are not necessarily mobile. They also prove to be a problem with the issue of privacy. People are not comfortable with the intrusion. There have been strides to manage the timing and only capturing data when needed but the issue remains.

Audio signals help with activity recognition, for example, the sound of turning pages could indicate reading, the crunching sound of eating, etc. The sounds could also provide the information about the environment and place and thus helping with matching the activity in context with the environment.

Object Use [48, 49] study the use of RFID tag readers to interpret household activities, by installing RFID tags on household items and readers on the individual so that when that person interacts with the said object, it logs it as the activity done, such as doing laundry, making coffee, etc. Another approach could be to install contact or binary switches to sense the activity - for example the opening and closing of the door or cabinet - and installing a wireless system to recognize high-level activities. [50]

Radio-based Sensing Use of radio sensors where one does not have to carry a device on his person for detection, instead studying the interruption of signals between transmitter and receiver - example when a person crosses a door. Not much work has been done using this technology, [51] was able to detect two activities of 'walking' and 'talking on mobile phone' with the setup done in a office doorway.

Combination Sensors The best results are achieved by using a combination of sensors to log data. Using GPS sensors with other sensors help with the activity recognition better as it tells if the activity is performed indoors or outdoors, or in which room of the house [52]. Combination of physiological sensors and inertial sensors help with measuring the intensity of the workout or the energy expended during that particular activity [53]. Image and audio sensors combined provide more concrete conclusion than using just one.

Besides these there are many more type of sensors which are used for specific fields; for example, sensors for body temperature, muscle contractions, optical, etc.

2.4 Methods

There is a lot of work done on different approaches in human physical activity recognition.

Mainly, the bulk of the work is done on following methods for supervised machine learning:

- Distance based methods: K-Nearest Neighbors (k-NN)
- Decision tree based methods: CART, ID3, C4.5, custom generated trees
- Statistical methods: Naive Bayes' classifier, Linear discriminant analysis (LDA) technique
- Kernel methods: Support Vector Machine (SVM)
- Ensemble methods: Random trees, extra trees
- Deep learning: Deep neural network (DNN), Artificial neural network (ANN)

2.4.1 K-Nearest Neighbors

KNN is a distance based machine learning algorithm used for classification or regression problems. It is one of the most basic and most used supervised learning algorithms. It is based on the theory that *birds of a feather flock together*; i.e. the assumption that similar things are in close proximity. KNN classifies data points based on closest training instances by voting of the neighbors and determining which class the data point belongs to. [45, 54–57] are a few who have used KNN method for the purpose of activity recognition. Determining the value of k is a trial and error process, we check with various values to see which gives the most accurate results. [58] gets an accuracy of 97.65 with k = 3. [59] used the default scikit-learn parameters(k = 5 nearest neighbors, uniform weights and p = 2 for Minkowski metric) and according to their observation KNN performed better than C4.5 decision tree. Supporting this [53] also got a score of 87.62 percent accuracy using the Weka toolkit [60] as opposed to 85.03 percent of C4.5.

2.4.2 Decision Trees

Decision trees are widely used technique for machine learning. It is a predictive model where a target value is predicted based on other input/training values. It splits a data based on various conditions. There are many different algorithms for decision trees, and many of them are used for different problems to machine learning.

CART can be used as standalone (as done by [61]) or in conjunction with other algorithms. [58] uses CART algorithm on different datasets with varying percentages of training data. On PAMAP2 with 50 percent training data, he gained accuracy of 94.5 percent.

C4.5 is used by [53] with 85.03 percent accuracy with the help of Weka toolkit. [59] uses an optimized version of it but the results were not above those of other methods. [56, 62, 63] have also used C4.5 in their work on activity recognition.

2.4.3 Random Forest

Random forest is an ensemble method of different decision trees in random order, forming a 'forest'. When splitting a node while forming trees, random forest algorithm chooses the best feature from a random subset of features. This renders random forest to be a very stable and well-performing method in some areas. [58] gained an accuracy of 98.05 percent using 50 percent of training data for random forest.

2.4.4 Linear Discriminant Analysis

LDA is a great supervised machine learning algorithm used in characterization or separation of classes. It works by making predictions that which class the set of inputs belong to. It works great with some specific problems with continuous predictors. [64] used LDA for image feature extraction and [65] has used it for speech recognition. . Working with PAMAP2 dataset and 50 percent training data [58] gained 64.47 percent accuracy using LDA.

Quadratic discriminant analysis (QDA) is a derivative of LDA also used for classification. QDA is use by [66] in bioinformatics and by [67] in molecular physics.

2.4.5 Other Methods

The above mentioned methods are supervised machine learning techniques. Supervised learning is learning with supervision which translates to using labeled data to train your project. Majority of the work done for activity recognition is based on supervised techniques. There are also some unsupervised or semi-supervised techniques that have been used with success. In unsupervised learning we work with unlabeled data.

Chapter 3

Dataset for Physical Activity Monitoring

For a list of all the ways technology has failed to improve the quality of life, please press three.
— *Alice Kahn*

3.1 Introduction

Our thesis is about analyzing the data we get from wearables. The dataset we are exploring is PAMAP2 Physical Activity Monitoring Dataset. It is an open source dataset made available at UCI repository [68].

This dataset is chosen because of extensive physical activities: both everyday household and sports, performed by 9 subjects wearing 3 IMUs (Inertial Measurement Units) and a heart rate monitor.

3.2 Data Collection

The data is collected from 9 test subjects, 8 male and 1 female. All of them were aged 27.22 +/- 3.31 years with BMI ranging 25.11 +/- 2.62 kgm^{-2} [69].

Three inertial measurement units (IMUs) and a heart rate monitor were worn by these subjects. Sampling frequency of the IMUs is 100Hz; i.e. data is collected at every 0.01 second. The sampling frequency of heart rate monitor is 9Hz.

The placement of the IMU sensors was: [68]

- 1 IMU over the wrist on the dominant arm
- 1 IMU on the chest
- 1 IMU on the dominant side's ankle

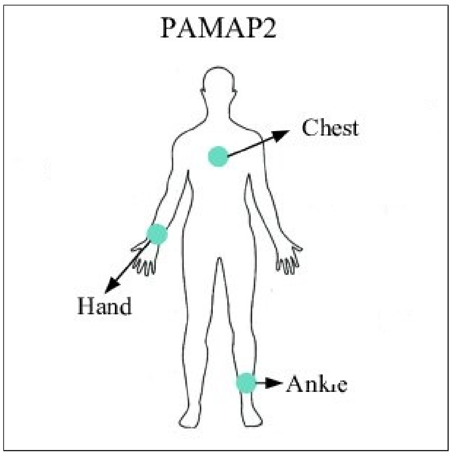

Figure 3.1: Positions of the IMUs in PAMAP2

The participants had to perform 12 protocol and 6 optional activities. The list of activities is given in Table 3.1

Protocol Activities	Optional Activities
Lie	Watching TV
Sit	Computer Work
Stand	Car Driving
Iron	Folding laundry
Vacuum clean	House cleaning
Descend stairs	Playing soccer
Ascend stairs	
Normal walk	
Nordic walk	
Cycle	
Run	
Rope jumping	

Table 3.1: Activities performed by the test subjects

These activities and their mapping is given in the dataset by [68]

3.3 Data Format

The dataset contains two sub-folders: Protocol and Optional. In addition to that following five pdf files are included:

- readme
- DataCollectionProtocol
- DescriptionOfActivities
- PerformedActivitiesSummary
- subjectInformation

The titles of the files are self-explanatory.

The protocol folder contains information from all 9 subjects, whereas, the optional folder contains data from only five test subjects.

All files contains data in 54 columns. The distribution of information in columns, as described in [68], is given in 3.2

ID	Description
1	timestamp (s)
2	activityID
3	heart rate (bpm)
4-20	IMU hand
21-37	IMU chest
38-54	IMU ankle

Table 3.2: PAMAP2 columns

The activitiesID is int64, and the rest of the 53 columns are float64 format.

Table 3.3 provides further explanation on the IMU columns.

ID	Description
1	temperature (°C)
2-4	3D-acceleration data (ms^{-2}), scale: $\pm 16g$, resolution: 13-bit
5-7	3D-acceleration data (ms^{-2}), scale: $\pm 16g$, resolution: 13-bit
8-10	3D-gyroscope data (rad/s)
11-13	3D-magnetometer data (μT)
14-17	orientation

Table 3.3: PAMAP2 attributes extracted from IMUs

Protocol folder contains 2872533 entries, total combined data of all subjects. We know that we should ignore the transitional entries, with activityID = 0, so after that we are left with 1942872 rows.

Number of data entries per test subject can be seen in the Figure 3.2

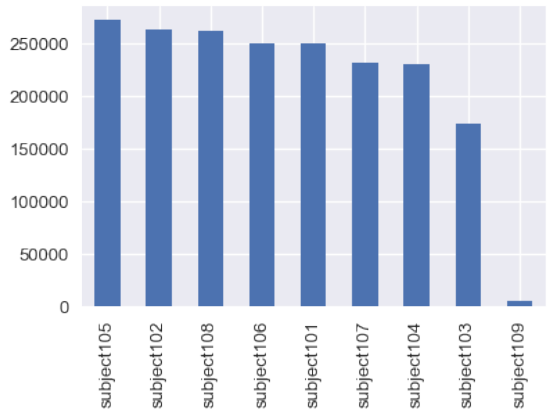

Figure 3.2: Number of protocol activities performed by subjects

3.4 Data Summary

Performed Activities Using crosstab function of the Pandas we have created the summary of the activities performed by the test subjects. Table 3.4 shows the total number of activity samples collected from each subject. The samples were collected at 0.01 seconds.

activityID	1	2	3	4	5	6	7	9	10	11	12	13	16	17	18	19	20	24	All
subject																			
subject101	27187	23480	21717	22253	21265	23575	20265	83646	0	54519	15890	14899	22941	23573	27114	54089	0	12912	469325
subject102	23430	22345	25576	32533	9238	25108	29739	0	0	0	17342	15213	20683	28880	0	0	0	13262	263349
subject103	22044	28761	20533	29036	0	0	0	0	0	0	10389	15275	20325	27975	0	0	0	0	174338
subject104	23047	25492	24706	31932	1	22699	27533	0	0	0	16694	14285	20037	24995	0	0	0	0	231421
subject105	23699	26864	22132	32033	24646	24577	26271	0	110883	0	14281	12727	24445	33034	0	28488	0	7733	411813
subject106	23340	23041	24356	25721	22825	20486	26686	0	61777	0	13291	11272	21078	37744	21786	28714	0	256	362373
subject107	25611	12282	25751	33720	3692	22680	28725	0	0	0	17646	11618	21552	29499	0	0	0	0	232776
subject108	24165	22923	25160	31533	16532	25475	28888	0	68725	0	11683	9655	24292	32990	23650	41691	18126	8806	414294
subject109	0	0	0	0	0	0	0	0	68550	0	0	0	0	0	27328	34206	28789	6391	165264
All	192523	185188	189931	238761	98199	164600	188107	83646	309935	54519	117216	104944	175353	238690	99878	187188	46915	49360	2724953

Table 3.4: Performed activities summary

Figure 3.3 and 3.4 show the total number of times the activities samples were collected from the test subjects.

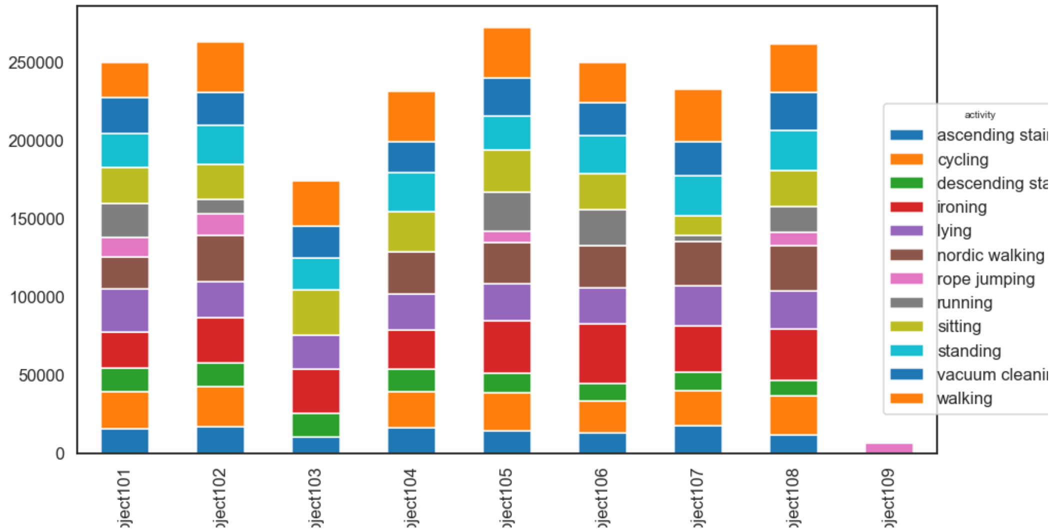

Figure 3.3: Performed activities summary stack graph

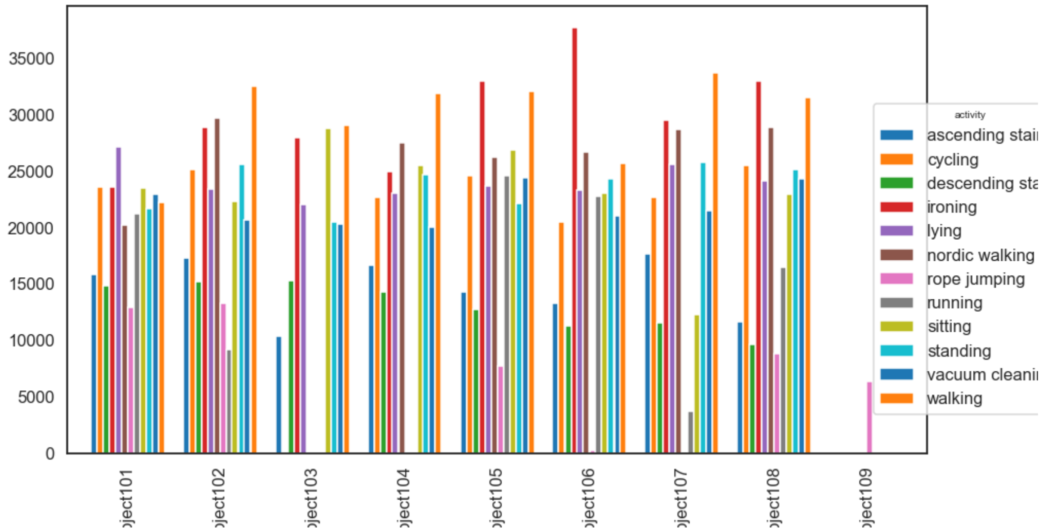

Figure 3.4: Performed activities summary bar plot

3.5 Data Cleaning

There is no substitute for getting to know your data. It is a time-intensive manual exercise. Investing the time up front to analyze your data to improve its quality and integrity always pays dividends in the latter phases of the project. [70]

Clean data is better than large data. A small cleaner data may give meaningful results with simple algorithms than a larger dataset with complicated algorithms. Therefore data cleaning is an important part of the project. There are different methods or steps to cleaning data.

3.5.1 Remove Duplicates

The first basic step is to remove the duplicate rows, if there are any, from the dataset. This can occur during data collection stage and is fairly easy to determine and fix.

3.5.2 Remove Timestamp

Another step to cleaning the data is to remove irreverent data; i.e. columns that do not provide any meaningful information to reach our desired result. We have removed timestamp column because it could bias the classifier performance by artificially increasing it, since subjects follow a protocol in which all activities are timed. By removing this feature, the classification will only rely on the sensors data. [71]

3.5.3 Remove Orientation

The orientation columns, which are 4 per IMU (12 total), will be removed as they do not provide valid data as mentioned by the dataset collection author [68].

3.5.4 Remove Subject 109

We will ignore the data from subject 109 as we can see from the Table 3.4 that it performs only one activity, the rest of the data is missing - either due to miscommunication or faulty connection while recording the data by the authors of dataset.

3.5.5 Handle Missing Values

Missing values appear as NaN, blanks or dashes. They are very easy to find in the dataset but the question is how to handle them. Missing values can be completely random or they could be systematically missing for a reason.

There are numerous methods to deal with missing values: do nothing, remove the entire row, imputing/replacing values based on other observations - threshold, mean or median value. We can also set a threshold for the number of values in an instance to be missing before dropping the row; for example, if the row is missing 3 or more values then drop the row.

We should always drop the instances only if the dataset integrity is increased. Always dropping the row might not be in best practice, as we may miss some meaningful randomness.

In our thesis we see that about 90 percent of the heart rate data is missing because of the difference of the sampling frequency of IMUs and heartrate sensor. In case of heartrate column we have filled the missing values with bfill (i.e. a technique used to fill the data from below row) as we assume that heartrate will not change drastically in 0.01 of seconds. As for the rest of the data, we have dropped the rows with missing values.

3.5.6 Removing Outliers

Detecting and handling outliers is more difficult task than handling missing values and duplicates. Outliers are values distant from other observed values. But just because a value is an outlier doesn't mean its an erroneous value - they could prove to be very informative. They could be a mistake or show a variance in the data.

Removing an outlier should only be done when absolutely sure that it is a mistake and can cause problem with our model. In a good trustworthy dataset the outliers should be rare - and thus should not have much statistical impact.

In case of qualitative data present in the dataset, we would have dealt with typographical errors and inconsistencies. But as discussed before, PAMAP2 is mostly a qualitative dataset.

Chapter 4

Feature Analysis and Classification

We live in a society exquisitely dependent on science and technology,
in which hardly anyone knows anything about science and technology.
— Carl Sagan

4.1 Introduction

In this thesis we attempt to classify the activities correctly from the raw data available. In Chapter 1 we have discussed the motivation for the work of this thesis. Chapter 3 explores the dataset used for this project: PAMAP2. The dataset provides us with 53 features (excluding time stamp). We are left with 40 features after the pre-processing in Chapter 3. In this chapter we will delve into extracting features for the classifiers and various classifier algorithms and compare their performance in identifying different physical activities. [41] and some other studies suggests that data from accelerometers is the best in identifying the activity as they respond quickly to activity change.

Figure 4.1 shows the raw acceleration (from chest IMU) and heart rate (in bpm) and we can see how they vary with four different activities (standing, cycling, running and walking)

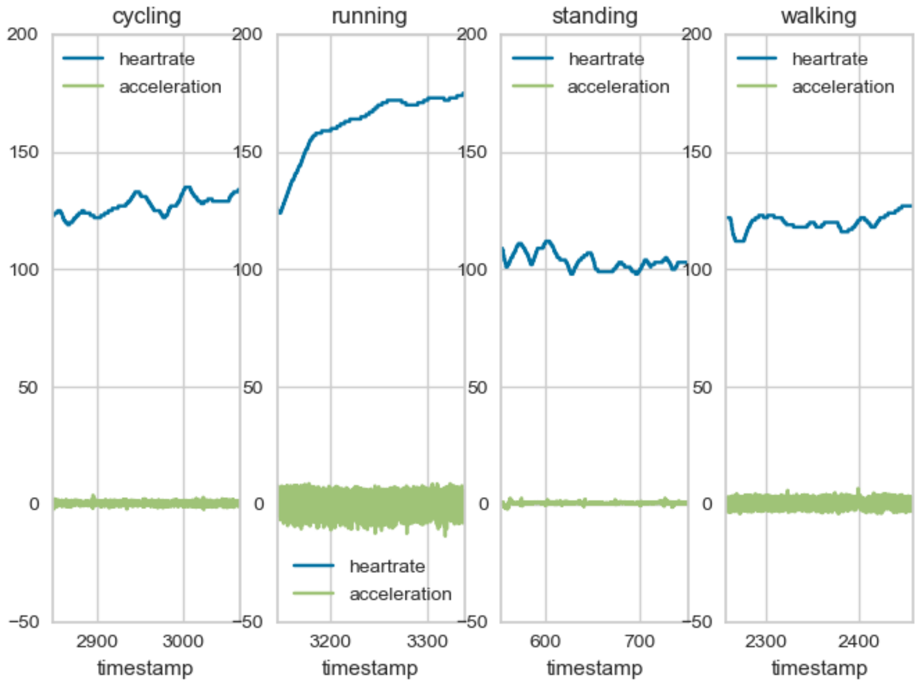

Figure 4.1: Raw acceleration (from chest IMU) and heat rate data from PAMAP2 dataset of four activities

4.2 Data Processing Chain

Figure 4.2 shows the basic HAR chain which is also adopted in this study.

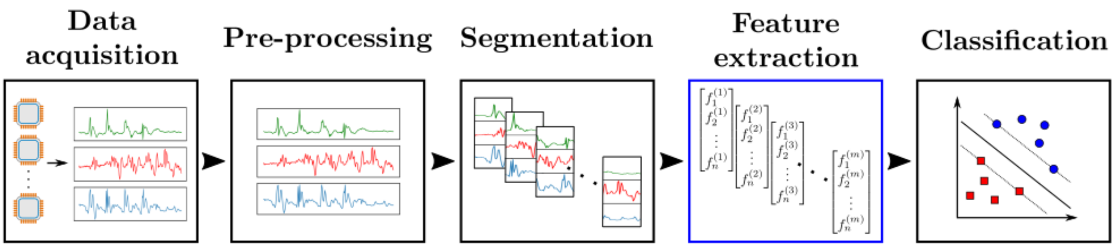

Figure 4.2: Data processing chain for Human activity recognition [72]

4.2.1 Data Acquisition

We are using the PAMAP2 open dataset. This data is collected from 9 subjects, wearing 3 IMUs and a heart rate monitor. Chapter 3 explores the dataset and its features.

4.2.2 Pre-processing

Data is pre-processed by (1) removing the unnecessary columns of time-stamp and orientation, (2) missing (NaN) or duplicated values are filled or removed, (3) transition activities are also removed. After this, we are left with 40 features.

All of the above mentioned steps are detailed in Chapter 3.

4.2.3 Segmentation

Features for the classification are typically computed over a sliding window. The sliding window length is usually fixed. Different window lengths are used by authors in various studies.

We have decided to take window size of 512 (5.12 seconds) which slides one instance (0.01 second) at a time.

4.2.4 Feature Extraction

Identifying suitable features for the classifiers is crucial for the correct identification of the target classes.

Most common features used for the acceleration data are mean, variance, standard deviation or discrete Fast Fourier transform (FFT) coefficients. Energy, entropy or peaks in data are commonly derived from FFT.

Features used in this thesis:

- Difference of absolute acceleration
- FFT amplitude peak of rotation rate

We compute the features over every window separately. But, before computing the features we will cut off first and last 1000 items, because of activity start and end transition period.

Difference of Absolute Acceleration

First features we explore is absolute acceleration, maximum and minimum acceleration and difference between max and min acceleration. We calculate absolute acceleration in order to get rid of the orientation.

Absolute acceleration:

$$|a| = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

where,

|a| = absolute acceleration,

a_x^2 = IMU chest acceleration in x-axis,

a_y^2 = IMU chest acceleration in y-axis,

a_z^2 = IMU chest acceleration in z-axis

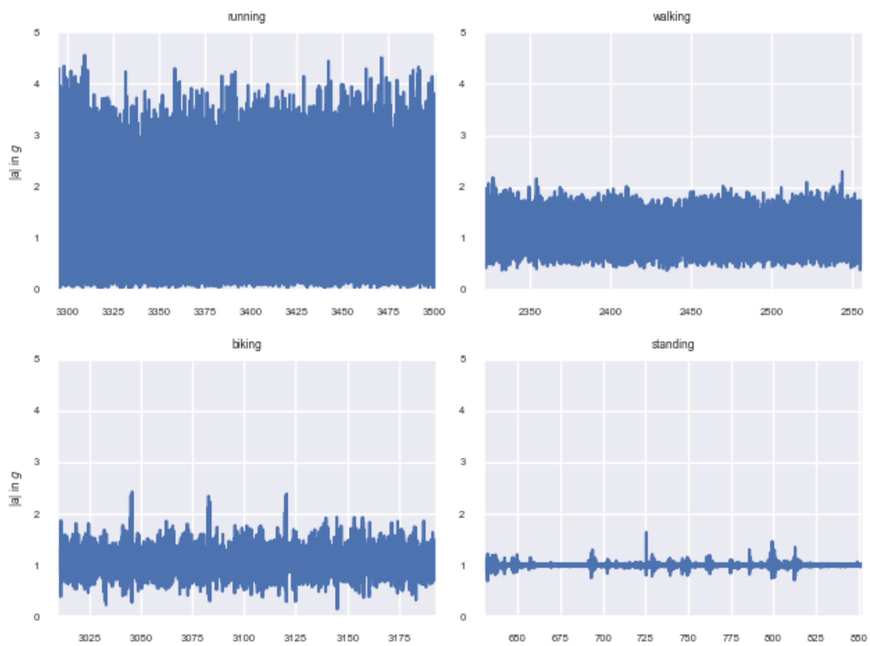

Figure 4.3: Absolute acceleration of four activities (running, walking, cycling/biking, standing)

From the absolute acceleration we will calculate maximum and minimum acceleration over the sliding window.

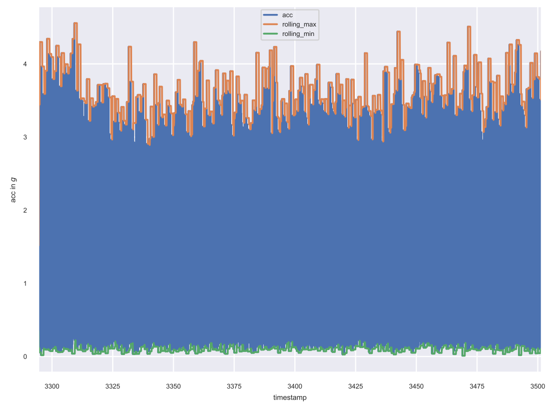

Figure 4.4: Rolling maximum and rolling minimum of absolute acceleration of running activity calculated over sliding window

Figure 4.4 shows the rolling maximum and rolling minimum of absolute acceleration of running activity calculated over sliding window.

Figure 4.5 shows the difference of maximum and minimum absolute acceleration.

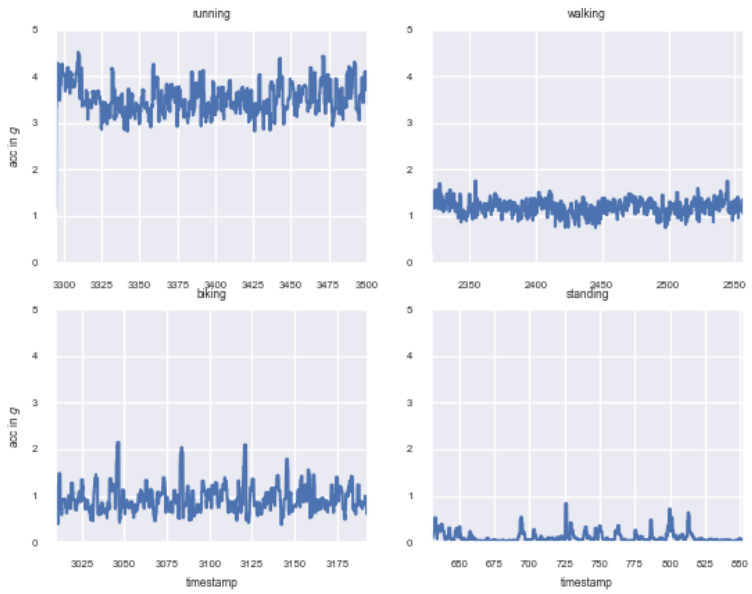

Figure 4.5: Difference of absolute acceleration of four activities (running, walking, cycling/biking, standing) calculated over sliding window

Now if we take a look at this feature and plot it as in figure 4.6 we can see that this feature provides us with pretty good separation between certain activities (like standing and running) but overlaps in others (walking and cycling). We need other features to separate them.

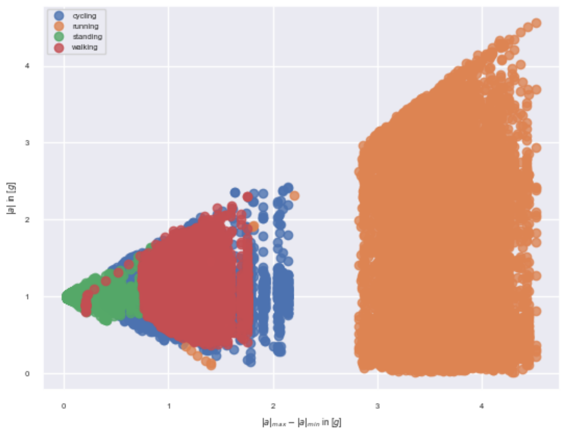

Figure 4.6: Plotting of absolute acceleration of four activities (running, walking, cycling/biking, standing) against difference in acceleration.

FFT Amplitude Peak of Rotation Rate

Because it is expected that a higher accuracy can be reached if each instance capture temporal information, we will compute the discrete Fourier transform (DFT) over the signal for every window and dimension separately using the fast Fourier transform (FFT) algorithm. [71]

We calculate FFT amplitude of rotation rate and check how it differentiates the activities. Figure 4.7 shows that it is a good feature for classification.

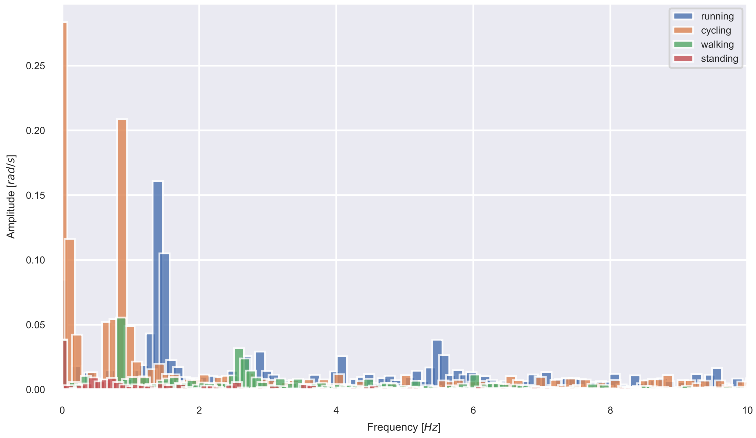

Figure 4.7: FFT amplitude of rotation rate of four activities (running, walking, cycling/biking, standing)

Using the method in Listing 4.1 we will calculate FFT amplitude peak of the rotation rate over the sliding window.

```
def fft_amplitude(s, kind='peak'):

    # windowing to get rid of the leakage effect
    hann = np.hanning(len(s))

    # FFT with Hanning Window
    Yhann = np.fft.fft(hann*s)

    N = int(len(Yhann)/2+1)
    Y = 2.0*np.abs(Yhann[:N])/N # right half (positive freqs only)

    # frequency axis, if needed
    fa = 1.0/dt
    f = np.linspace(0, fa/2.0, N, endpoint=True)

    if kind=='peak':
        return np.max(Y) # just return the maximum peak amplitude
    elif kind=='periodicity':
        return np.max(Y) / np.mean(Y) # return periodicity
    elif kind=='full':
        return f, Y # return the full spectrum
```

Listing 4.1: Code for calculating FFT amplitue

4.2.5 Classification

The last stage of data processing chain is classification. The goal of this thesis is to find a classifier which gives us the highest accuracy score. Therefore we will use multiple classifier algorithms to compare, analyze the result and chose the best one.

We have used several different classifiers mentioned in the referenced works for comparison. Below are listed some of the classifiers used.

- Simple algorithms like Naive Bayes, Decision Trees
- Ensemble algorithms: Bagging algorithms (Bagged Decision Tree, Random Forest, Extra Trees), Boosting algorithms (Stochastic Gradient Boosting, AdaBoost), and voting ensemble
- Others (Neural Net)

We will perform classification with the features extracted in previous section plus heart rate. We split the dataset into training set and testing set. We use 70 percent data for training the classifier and 30 percent to test the model as shown in Figure 4.8.

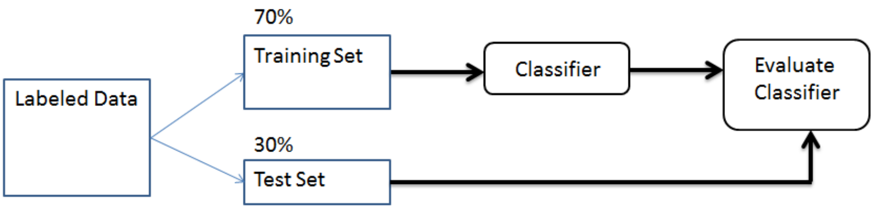

Figure 4.8: Schematic for training and testing data split for classification process [73]

We will use three main methods for classification validation:

- Single subject validation: training and testing from the data from a single subject.
- LOSO (Leave One Subject Out): training on data from all the subjects minus one, that one we will use for testing the model
- Cross-person validation: training on the data from one subject and testing it on data from another subject

In the next chapter we will look at the results of our classifier models and the metrics used to check the validity.

Chapter 5

Evaluation and Results

Technology is cool, but you've got to use it as opposed to letting it use you.

— Prince

In this chapter we will discuss the measures and the methodology used to evaluate our classifiers. The results are also presented in Section 5.2

5.1 Performance Evaluation

This section describes the metrics and the methods used for performance evaluation of the classifier models.

5.1.1 Performance Metrics

To evaluate our classifier models we will use multiple metrics of accuracy, precision, recall (sensitivity), and f1 score. We will explain in detail these metrics below but first we need to understand confusion matrix and its four parameters as seen in Figure 5.1.

- True Positive (TP): Correctly predicted positive values; i.e. actual class and predicted class are both true.

- True Negative (TN): Correctly predicted negative values; i.e. actual class and predicted class are both false.

- False Positive (FP): Incorrectly predicted positive values; i.e. actual class is false and predicted class is true.

- False Negative (FN): Incorrectly predicted negative values; i.e. actual class is true and predicted class is false.

		Predicted Class	
		Negative	Positive
Actual Class	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

Figure 5.1: Confusion matrix

Accuracy

Accuracy is the proportion of correctly predicted instances out of total number of predictions.

$$Accuracy = \frac{Number\ of\ correct\ classifications}{Total\ number\ of\ classifications}$$

Precision

Precision is a measure that tells us the accuracy or precision of our model from predicted instances, i.e. actual positives from the predicted positives.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$= \frac{True\ Positive}{Total\ Predicted\ Positive}$$

Recall

Recall calculates the proportion of true positives out of the total actual positives, i.e. how many actual positives our model captures through labeling it as Positive (True Positive).

$$\begin{aligned} Recall &= \frac{True\ Positive}{True\ Positive + False\ Negative} \\ &= \frac{True\ Positive}{Total\ Actual\ Positive} \end{aligned}$$

F1 Score

F1 score gives us the balance between Precision and Recall. It is a good measure when our data is unbalanced.

$$F1 = 2 * \frac{Precision\ *\ Recall}{Precision + Recall}$$

5.1.2 Evaluation Methods

In our thesis we have used three methods of validation.

- Single person validation
- Cross person validation
- LOSO: Leave One Subject Out

We will further explain these methods below.

Single Person Validation

In this validation method we will use the data of a single subject and split that data into training set and testing set. We will use the train set to train our model and test set to test the model.

Basically, training the model on the same person we are going to test it on. This method, as is observed in the Figure 5.2, gives us the highest accuracy.

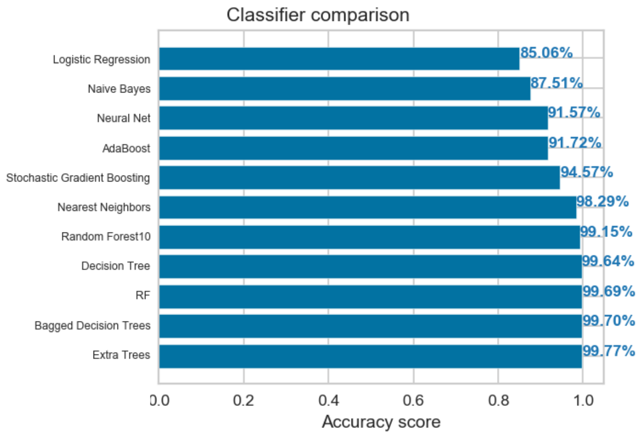

Figure 5.2: Preliminary classifier comparison performed on whole data with a single person validation

Cross Person Validation

In this we will perform validation by training the model on one subject and testing it on another, and so on.

Leave One Subject Out Validation

As we can tell from the name, the validation is performed by training the model by all subjects but one, and testing the model on that one subject.

5.2 Results

In this section we will present the results from our experimental evaluation of various classifier algorithms.

We can see from Figure 5.3 that for four selected activities of walking, running, cycling and standing, the selected features provide good decision boundaries for the classifier.

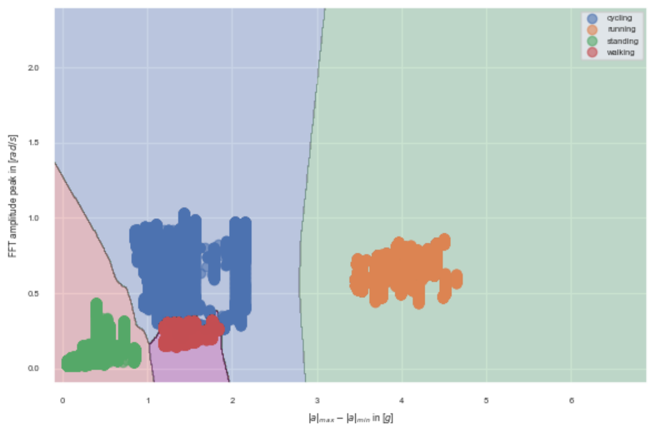

Figure 5.3: Decision boundaries of Support Vector Classifier with features for four different activities

As our data has unbalanced class distribution, accuracy is not necessarily the best of the metrics for evaluation due to the accuracy paradox.

The accuracy paradox is where our model gives us very high accuracy but it is actually only representing the class distribution. Therefore, we will also use other metrics mentioned in Section 5.1.1.

We have also balanced the training set using undersampling before training our models. From the preliminary classification comparison using the whole dataset (all subjects) and performing single person validation method we get the results shown in 5.2. Basing on the results we will choose six top classifiers for further validation.

For single subject validation we see that Extra Trees, Random Forest and Bagged Decision Trees perform best, with accuracy, balanced accuracy, f1 score, precision and recall given Table 5.4.

Leave One Subject Out performs best on Stochastic Gradient Boosting, Bagged Decision Trees and Random Forest, with results shown in Table 5.5.

Cross person evaluation performs best on kNN, Extra Trees and Stochastic Gradient Boosting as shown by results in Table 5.6.

We are also calculating balanced accuracy along with normal accuracy because as discussed before accuracy scores can not be trusted with unbalanced data as such that we have.

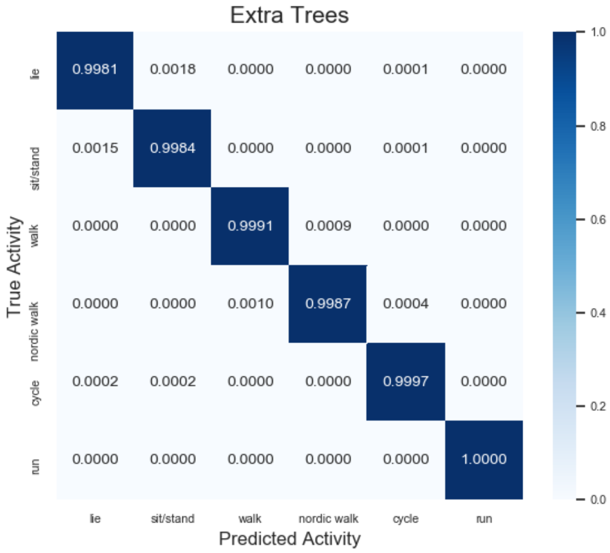

Figure 5.4: Confusion Matrix for Extra Trees Classifier with Single Person Validation

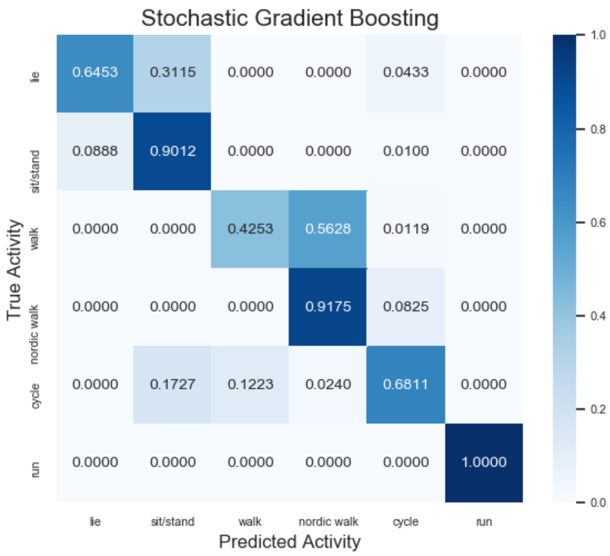

Figure 5.5: Confusion Matrix for Stochastic Gradient Boosting Classifier with LOSO Validation

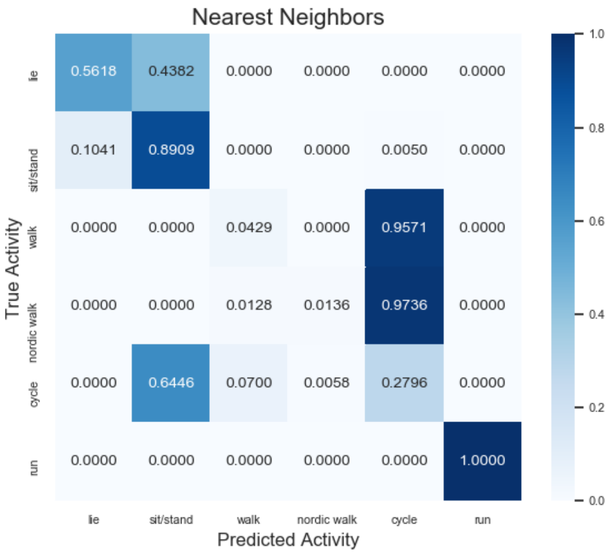

Figure 5.6: Confusion Matrix for K Nearest Neighbors Classifier with Cross Person Validation

Furthermore, confusion matrices as shown in Figures 5.4, 5.5 and 5.6, give us a more detailed look at the validity of the model.

We can see from the above results that training a model on a single person and testing it on the same person gives us a almost perfect accuracy score, followed by Leave One Subject Out method. Cross Person method comes in last because there is not sufficient training data.

	precision	recall	f1-score	support
cycle	1.00	1.00	1.00	6174
lie	1.00	1.00	1.00	7375
nordic walk	1.00	1.00	1.00	5223
run	1.00	1.00	1.00	5429
sit/stand	1.00	1.00	1.00	12594
walk	1.00	1.00	1.00	5615
micro avg	1.00	1.00	1.00	42410
macro avg	1.00	1.00	1.00	42410
weighted avg	1.00	1.00	1.00	42410

Table 5.1: Breakdown of classifier scores for each class for Extra Trees Classifier with Single Person Validation

	precision	recall	f1-score	support
cycle	0.82	0.68	0.74	6174
lie	0.81	0.65	0.72	7375
nordic walk	0.59	0.92	0.72	5223
run	1.00	1.00	1.00	5429
sit/stand	0.77	0.90	0.83	12594
walk	0.76	0.43	0.55	5615
micro avg	0.78	0.78	0.78	42410
macro avg	0.79	0.76	0.76	42410
weighted avg	0.79	0.78	0.77	42410

Table 5.2: Breakdown of classifier scores for each class for Stochastic Gradient Boosting with LOSO Validation

	precision	recall	f1-score	support
cycle	0.14	0.28	0.19	6174
lie	0.80	0.55	0.65	7375
nordic walk	0.58	0.01	0.02	5223
run	1.00	1.00	1.00	5429
sit/stand	0.61	0.91	0.73	12594
walk	0.22	0.02	0.04	5615
micro avg	0.54	0.54	0.54	42410
macro avg	0.56	0.46	0.44	42410
weighted avg	0.57	0.54	0.50	42410

Table 5.3: Breakdown of classifier scores for each class for K Nearest Neighbors Classifier with Cross Person Validation

Classifier	Accuracy	Balanced Accuracy	F1 Score	Precision	Recall
Stochastic Gradient Boosting	96.913464	97.416094	97.416094	97.288307	97.416094
Extra Trees	99.884461	99.895681	99.895681	99.894706	99.899317
RF	99.790144	99.809351	99.809351	99.795843	99.808373
Bagged Decision Trees	99.794860	99.808267	99.808267	99.801266	99.808267
Nearest Neighbors	98.943645	99.095224	99.095224	99.004769	99.095224
Decision Tree	99.728838	99.740900	99.740900	99.733874	99.731039

Table 5.4: Accuracy, balanced accuracy and F1 scores of the classifier models for Single Person validation method

Classifier	Accuracy	Balanced Accuracy	F1 Score	Precision	Recall
Stochastic Gradient Boosting	77.630276	76.172711	76.172711	79.156736	76.172711
Extra Trees	68.464985	66.302506	66.302506	68.300071	66.355928
RF	69.254893	67.177181	67.177181	67.733935	66.584767
Bagged Decision Trees	68.818675	66.801627	66.801627	68.140938	66.801627
Nearest Neighbors	67.375619	66.220074	66.220074	66.908643	65.273229
Decision Tree	68.118368	65.273229	65.273229	67.289369	65.939624

Table 5.5: Accuracy, balanced accuracy and F1 scores of the classifier models for Leave One Subject Out validation method

Classifier	Accuracy	Balanced Accuracy	F1 Score	Precision	Recall
Stochastic Gradient Boosting	53.947182	45.911178	45.911178	55.793707	45.911178
Extra Trees	54.164112	46.545636	46.545636	55.898409	46.431887
RF	52.329639	44.771112	44.771112	52.892070	44.675985
Bagged Decision Trees	52.204669	44.652714	44.652714	52.882016	44.652714
Nearest Neighbors	53.831643	46.478951	46.478951	58.308299	46.478951
Decision Tree	52.725772	45.167573	45.167573	53.357199	45.050139

Table 5.6: Accuracy, balanced accuracy and F1 scores of the classifier models for Cross Person validation method

Chapter 6

Conclusion and Future Directions

Success in creating AI would be the biggest event in human history. Unfortunately, it might also be the last, unless we learn how to avoid the risks.
— Stephen Hawking

Human activity recognition is a field which benefits many areas of life. The goal of the thesis was to successfully classifying various everyday life ADL activities as motivated by reasons discussed in Chapter 1.

6.1 Conclusion

In this thesis, we have used PAMAP2 dataset which comprises of 9 subjects performing 12 protocol activities over a period of 10 hours.

First we pre-processed the raw data by removing unnecessary data and filling in missing values. Then, we extracted the features from time and frequency domain to use in the classifier models. Finally we performed classification on the transformed data.

Validation of the the selected model has been done by methods of single person, cross-person and LOSO. Multiple performance metrics have been used for evaluating the classifier models.

We have managed to achieve considerable accuracy in our thesis but further work needs to be done as there is a lot more scope in this field that we must explore. We will discuss the future direction this work can take in the next section.

6.2 Future Direction

Intensity Estimations

Next step is to recognize the intensity of the activities as done in [53] Heartbeat or other physiological data can be used to measure the intensity of the activity being performed.

Recognition of High Level Activities

We can use the recognition of the low level activities (as such done in this thesis) to help us with the recognition of high-level activities.

Towards this direction considerable work has been done by [45].

More Data

More data need to be collected with more subjects and over longer period of time. We were limited by unbalanced data where some classes had more/sufficient data while others had very small amount in comparison.

Multiple datasets should be used to validate the robustness of the selected model.

Feature Extraction and Analysis

In our thesis we have worked with limited number of features for classification, but more work needs to be done in order to gain better accuracy and scores with selection of optimal features. In [71] the authors have focused mainly on feature selection.

Semi supervised model

Most of the work done on activity recognition is done on annotated data and with supervised learning.

Un-annotated data is easier to collect than labeled data. These days with wearable technology many un-annotated datasets are available which can be used to test and create a unsupervised or semi supervised model. As discussed in [8] semi supervised learning is gaining more popularity among businesses and researchers.

Some researchers have implemented semi supervised learning with considerable success [74–76]

Activity Quality

If we can manage to capture and recognize not only what activity has been performed but also how well it has been performed, then that could open new doors for various applications.

Major impact will be in sports an fitness field, where athletes or individuals could monitor how well they are training or performing.

It could also prove useful in health field with elderly living assistance and rehabilitation patients.

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Appendix A

Brief description of the 18 different performed activities

lying: lying quietly while doing nothing, small movements – e.g. changing the lying posture – are allowed

sitting: sitting in a chair in whatever posture the subject feels comfortable, changing sitting postures is also allowed

standing: consists of standing still or standing still and talking, possibly gesticulating

ironing: ironing 1-2 shirts or T-shirts

vacuuming: vacuum cleaning one or two office rooms (which includes moving objects, e.g. chairs, placed on the floor)

ascending stairs: was performed in a building between the ground and the top floors, a distance of five floors had to be covered going upstairs

descending stairs: was performed in a building between the ground and the top floors, a distance of five floors had to be covered going downstairs

normal walking: walking outside with moderate to brisk pace with a speed of 4-6km/h, according to what was suitable for the subject

Nordic walking: was performed outside on asphaltic terrain, using asphalt pads on the walking poles (it has to be noted, that none of the subjects was very familiar with this sport activity)

cycling: was performed outside with a real bike with slow to moderate pace, as if the subject would bike to work or bike for pleasure (but not as a sport activity)

running: meant jogging outside with a suitable speed for the individual subjects

rope jumping: the subjects used the technique most suitable for them, which mainly consisted of the basic jump (where both feet jump at the same time over the rope) or the alternate foot jump (where alternate feet are used to jump off the ground)

watching TV: watching TV at home, in whatever posture – lying, sitting – the subject feels comfortable

computer work: working normally in the office

car driving: driving between office and subject's home

folding laundry: folding shirts, T-shirts and/or bed linnens

house cleaning: dusting some shelves, including removing books and other things and putting them back again onto the shelves

playing soccer: playing 1 vs. 1 or 2 vs. 1, running with the ball, dribbling, passing the ball and shooting the ball on goal

Appendix B

Subject Information

Subject Information

Subject ID	Sex	Age (years)	Height (cm)	Weight (kg)	Resting HR (bpm)	Max HR (bpm)	Dominant hand
101	Male	27	182	83	75	193	right
102	Female	25	169	78	74	195	right
103	Male	31	187	92	68	189	right
104	Male	24	194	95	58	196	right
105	Male	26	180	73	70	194	right
106	Male	26	183	69	60	194	right
107	Male	23	173	86	60	197	right
108	Male	32	179	87	66	188	left
109	Male	31	168	65	54	189	right

Appendix C

Performed Activities Summary

Activities performed by subjects (in seconds)

	subject101	subject102	subject103	subject104	subject105	subject106	subject107	subject108	subject109	Sum	Nr. of subjects
1 – lying	271.86	234.29	220.43	230.46	236.98	233.39	256.1	241.64	0	1925.15	8
2 – sitting	234.79	223.44	287.6	254.91	268.63	230.4	122.81	229.22	0	1851.8	8
3 – standing	217.16	255.75	205.32	247.05	221.31	243.55	257.5	251.59	0	1899.23	8
4 – walking	222.52	325.32	290.35	319.31	320.32	257.2	337.19	315.32	0	2387.53	8
5 – running	212.64	92.37	0	0	246.45	228.24	36.91	165.31	0	981.92	6
6 – cycling	235.74	251.07	0	226.98	245.76	204.85	226.79	254.74	0	1645.93	7
7 – Nordic walking	202.64	297.38	0	275.32	262.7	266.85	287.24	288.87	0	1881	7
9 – watching TV	836.45	0	0	0	0	0	0	0	0	836.45	1
10 – computer work	0	0	0	0	1108.82	617.76	0	687.24	685.49	3099.31	4
11 – car driving	545.18	0	0	0	0	0	0	0	0	545.18	1
12 – ascending stairs	158.88	173.4	103.87	166.92	142.79	132.89	176.44	116.81	0	1172	8
13 – descending stairs	148.97	152.11	152.72	142.83	127.25	112.7	116.16	96.53	0	1049.27	8
16 – vacuum cleaning	229.4	206.82	203.24	200.36	244.44	210.77	215.51	242.91	0	1753.45	8
17 – ironing	235.72	288.79	279.74	249.94	330.33	377.43	294.98	329.89	0	2386.82	8
18 – folding laundry	271.13	0	0	0	0	217.85	0	236.49	273.27	998.74	4
19 – house cleaning	540.88	0	0	0	284.87	287.13	0	416.9	342.05	1871.83	5
20 – playing soccer	0	0	0	0	0	0	0	181.24	287.88	469.12	2
24 – rope jumping	129.11	132.61	0	0	77.32	2.55	0	88.05	63.9	493.54	6
Labeled total	4693.07	2633.35	1743.27	2314.08	4117.97	3623.56	2327.63	4142.75	1652.59	27248.27	
Total	6957.67	4469.99	2528.32	3295.75	5295.54	4917.78	3135.98	5884.41	2019.47	38504.91	

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