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# Smartphone Supported Activity Level Estimation

Master thesis

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## Abstract

**Objective:** This thesis deals with the prototypical implementation of activity zone monitoring using the mobile phone. It uses the mobile phone sensors especially the accelerometer sensor to establish four types of motions and through a corresponding analysis with heart rate monitoring equipment, and then establishes the intensity of the activity. The goal behind the activity zone estimator as being suggested in this thesis is to provide notions of an activity of a certain intensity by only using the mobile phone without using external sensors. The implementation is based on first an analysis of existing technologies both when it comes to programming and when it comes to applications being available for mobile phones, and our implementation analysis then points out that the accelerometer is well tailored to establish an activity zone. However, the challenges might still occur with respect to, for example, the position of the smartphone on user's body, elevation of the ground where user performs the activity, and battery life time.

The objective of this thesis is to establish a prototypical implementation of mobile sensors to collect activity information from the users. This is done by creating the state of the art overview of mobile supported activity monitoring technologies. Our prototypical implementation is called *zonEstimator (ZE)* that classifies acceleration data into four states of motion; slow walking, fast walking, slow running and fast running, and through the states of motion indicates the activity zone and the activity intensity. To analyse the correlation between heart rate values retrieved by an external device (*Zephyr* sensor device) and acceleration results collected by the user's mobile phone sensors. To examine how much we can get about a user's activity zone by benefiting from only built-in accelerometer sensor of a smart-phone without using an external sensor in his daily life.

**Setting:** The components used in this thesis are a smart phone with the internal accelerometer sensor, both used for data collection and analysis, and an external heart rate sensor being used for having the de facto measurement of the heart rate intensity, and thus being able to correlate the mobile phone reported values with the measured heart rate values.

The developed application consists of three main modes; training, application, and reporting. The training mode includes both the heart rate sensor and internal accelerometer sensor, and this is the first step to create the aforementioned correlation between accelera-

tion and heart rate measurements. The application mode hosts only the built in sensor of the smart phone, which is to provide the real time results of activity zone of the user, and the reporting mode is to provide history of the results for the user.

**Results:** The accuracy of using built-in sensors for detecting the activity zone of a user changes under some specific circumstances. These relate to the position of the smart-phone on user's body, the slope of the ground where the activity is performed, physical condition of the user and some other factors. The accuracy of the detection is about 90% when the user carries the phone by his palm while it is greater than about 75% when it is carried by an arm band for fast walking and slow running activity types. We have found out that average acceleration goes up about 0.14 for each heart beat, meaning that as the intensity of the activity increases acceleration increases as well for the aforementioned activity types.

**Conclusions:** We have observed a strong correlation between the acceleration of the smart phone and heart rate measurements of the user when performing the following activities; slow walking, fast walking, slow running and fast running. The accuracy of the correlation is strongly associated with the position of the phone, and the incline of the ground where the user performs the activity. Plus, training phase is vital for accurate conclusions since the results vary from user to user in terms of age, sex, height, weigh and from smart phone to smart phone. Our analysis thus shows that the smart phone supported activity monitoring needs a training set per user.

Potential way ahead would be to use mobile phone sensors to establish a better judgement of the activity and then fine grained analysis to establish the zone estimator. Our recommendation is that multi sensor analysis is fits well in order to find out what the user is doing whether walking or running. However, it might be heavy for the mobile phone to measure accelerometer sensor data all the time. Therefore, there might be the idea of using an external accelerometer sensor such as the accelerometer that the Fitbit device uses, that could be used for getting a better idea of intensity of the activities. However, we may have the problem of Bluetooth this time, which might be an interesting discussion which one may look into.

## **Acronyms**

**AZ** Activity Zone

**HR** Heart Rate

**CA** Context Aware

**BPM** Beat per Minute

**PA** Physical Activity

**MET** Metabolic Equivalent of Task

**EE** Energy Expenditure

**ZE** Zone Estimator

**BMI** Body Mass Index

**WHO** World Health Organization

**SD** Secure Digital Memory Card

**GPS** Global Positioning System

**LE** Low Energy

**OS** Operating System

**API** Application Programming Interface

**SDK** Software Development Kit

**IC** Indirect Calorimetry

**DLW** The Doubly Labelled Water Method

**ALE** Activity Level Estimator

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# 1 Introduction

In this paper, we present our research on a mobile phone application that detects the Activity Zone (AZ) of a user without having to use any external sensor. Activity zone is a new term that we present in this study, which relates to the connection between heart rate measurements and activity of the user. An external heart rate (HR) sensor is used only for the training phase. It runs simultaneously with an accelerometer sensor of a smart phone in order to analyse the correlation among them for later purposes. Thanks to the correlation created in the training phase, the application “zonEstimator (ZE)” is able to estimate activity zone of the user by utilizing only the built-in accelerometer of the phone.

This section provides a short introduction to the area and explains what triggered us to conduct this study as well as the methods used during the study.

## 1.1 Motivation

Mobile devices are powerful means of diffusing knowledge. Notebooks, PDAs, smart phones, pervasive systems have already penetrated our lives and they are becoming more and more popular day by day. The term “pervasive” implies the assimilation of devices in the users’ daily life. The main purpose of pervasive devices is to provide users with being able to focus on their tasks rather than technical issues. Context-aware or sentient systems are also a part of pervasive computing. The term “context-aware” introduced first in Schilit and Theimer (1994), and Want et al. (1992) introduced one of the first context-aware applications that is “Active Badge Location System” that is based on infrared technology determining a user’s current location and redirecting phone calls to a telephone near to the user [1].

Context aware (CA) applications are widely in demand and easy to develop by means of the penetration of sensor technology and the access to open-source operating systems in smart phones. CA applications aim to adapt the application to different circumstances by using sensors and operational log data in general. Context refers to the time, location, activity and so forth. By this way, CA applications provide the user with information and services without asking for user’s intervention [2].

There are different types of CA systems which serve for different purposes.

Each of these systems may focus on monitoring only a specific context such as environmental context (level of humidity) or combination of classes such as physiological (blood pressure and BPM measurements) and behavioural context (running). Health and wellness monitoring is one example of CA monitoring. With long-term patient monitoring, doctors are able to obtain greater knowledge and to be more proactive about a patient's conditions and also to perform convenient interventions when needed [3]. Wellness in this context covers vital signs, patterns of sleep and daily activities. The main goal of wellness monitoring is to promote the current state of health. Healthy people need to protect or even promote their health conditions by doing exercise, eating healthy, sleeping well and managing their weight [4].

Our application which we will go into detail later in this paper is a kind of wellness monitoring application which encourages to be physically active and might provide useful information to both the patient and the doctor. As provided in [5], physical activities have direct effects on the normal vital signs. For instance, normal HR or in another words normal beat per minute (BPM) while running is higher than while walking, which indicates that the running activity requires more energy than the walking activity. In this paper, we aim to show the correlation between HR and accelerometer values of the smart phone of the user, and to discuss how much we can get about the activity level of the user by using only built-in accelerometer sensor of the smart-phone.

## 1.2 Methods

This section aims to provide a clear understanding of the scientific procedure consisting of prototypical implementation to test our hypothesis. This section provides information for understanding how subjects or objects were used when answering the question, what and how measurements were made, and how the analysis of the data were made. We follow the procedure provided and explained in [6] as our reference for this section.

Technological research differs from classical research for some aspects. The main purpose of technological research is to make further improvements for the existing technology or to come up with a new protocol or new hardware or a computer program [6]. The question arises here is if it is logical to follow classical research methods for a technological research. Some still argue that technology is not qualified as science, whereas most agree that computer science is qualified as such in terms of its nature which encapsu-

lates enough scientific features. This study is on computer science, with focus on life science supported by mobile devices. Though the meaning is called “science”, the methods in this study follow a technological approach. As suggested by Glass (1995), similar to a classical research paper, a life cycle of a technological research paper is typically consists of four phases.

**Informational Phase :** This phase is basically to provide information about the proposed technology by referring to the current state of art. In Section 4, literature and application review that relate to current problems, experiences and potential solutions in industry are provided for the sake of the Informational phase of our technological research.

**Propositional Phase :** The details of the hypothesis for the proposed technology is comprehensively predetermined by presenting scenario and focus group of our study. Section 2 “Scenario” of this paper includes the Propositional phase of our study.

**Analytical Phase :** This phase is where the hypothesis is analysed and a solution for the problem given is proposed. This phase is to explain if the model used in this study is understandable, and how it is deployed into practice. Section 3, 4, 5, and 6 encapsulate the requirements, implementation, implementation plan, technology selection aspects of the study provide the Analytical phase of our technological research.

**Evaluative Phase :** Section 7 of the thesis provides the Evaluative phase by presenting methodology in terms of validity, open issues and how it would be improved by refining the research questions and giving empirical feedback.

The study conducted by Tichy and his collaborators states that 70% of the papers they randomly selected in the area of computer science from the ACM were within design and modelling class that suggests new systems and in which the properties of techniques or models cannot be proven formally [7]. This thesis is also within design and modelling class and was created in company with the technological research method as explained above.

The anticipated work in this thesis is based on a mixture of science and technology. The scientific aspects of the study are as follows; constructing a hypothesis after a background research on the field, quantitative observation of the collected data in order to test the hypothesis, analysis of the

results and reaching a conclusion by comparing the results with the hypothesis. Technological aspects of the study also take part in scientific aspects as described above. The technological aspects include the use of a brand new smart phone equipped with sensor technology, an external HR sensor measuring the HR of the person and communicating with the smart phone, and prototypical implementation of a mobile-supported activity monitoring system.

However, we are introducing a new terminology of “activity zone”, indicating the intensity level of the action that the user takes, which would state how active or passive the user is considering his daily activities.

This paper is structured as follows. Section 2 introduces the terms that are used in the rest of the paper and provides an introduction to our study. By this section, we provided scenario, use cases and the focus group in order to clarify what we are out after by this study. In Section 3, we present the requirements and design parameters of our study. In Section 4, we describe current design principles and technological elements of context-aware monitoring systems. We discuss methods to measure activity, and real life activity monitoring applications as well as highlight advantages and disadvantages of them over each other in Section 5. We provide the implementation aspects of our study in Section 6, and provide the evaluation of our study based on different parameters in Section 7. Finally, we conclude our paper by giving the remarks and presenting some future work in this area.

## 2 Scenario

The following section provides a scenario for the utilization of our CA monitoring system with a brief description of whom and how we monitor as well as an explanation of the terms used in our scenario.

Physical activity (PA) is one of the most important motivations for people to maintain good health, to socialize, to get relaxed and lose tension, and to be physically in a good shape. That is why, a scenario about monitoring PA would be well applied for different types of people in the society such as elderly, obese people, people with cardiovascular diseases, people who have sedentary lifestyle, and so on. The studies given in [8] show that there is a close relationship between PA and prevention of diseases. Studies state that there are positive effects of increased physical activities on bone structure, cardiovascular diseases, body weight, normalizing insulin sensitivity and glucose tolerance. Studies no longer try to prove if there is any relation between PA and health, they focus on the nature of the relation instead. The report presented in [9] provides recommendations on the types and amounts of PA that healthy adults need. There are several aspects to explain at this point.

First, it is important to understand what kind of activity we do refer to when it is stated that PA has positive effects on human health. Essentially we can split physical activities into two groups as muscle strengthening such as weight-training program, and aerobic physical activities (also known as cardiovascular exercise or cardio). In our scenario, we take cardio exercises as our main activity type, the reason for this will be explained later in this chapter.

Second topic to be explained is activity intensity which will be referred as activity zone in our scenario. We may classify physical activities in three main groups in terms of intensity that is defined regarding increase and decrease of speed in HR. These are light (casual walking), moderate (Nordic walking) and vigorous intensity (Jogging). In order to promote and maintain health, and as well as associate with our scenario, we take into account two primary recommendations given in [9] for the healthy adults aged 18 to 65 years. The first one is to do a moderate-intensity endurance PA at least for 30 minutes on five days each week. The second one is to take vigorous-intensity activities for a minimum of 20 minutes on three days each week. Several combinations of these recommendations may also be performed in order to promote and maintain health, but it is not our focus in this paper.

Third, the amount of the activity, as explained with the term “Activity Dose”, is another important concept referred in the report of the American College of Sports Medicine and the American Heart Association [9]. Basically, a function of intensity, duration and frequency of PA gives us the total amount of that PA. By this metric, we could categorize if a person who performs a PA is active, moderately active, or inactive. The concept of metabolic equivalent of task (MET) which is based on energy expenditure is used to assign an intensity value to a specific activity. For instance, given that the duration and the frequency of the activities are the same, moderate-intensity activities like walking at 3.0 mph result in 3.0 to 6.0 METs, while the value of metabolic equivalent of task is greater than 6.0 for vigorous-intensity activities such as jogging. In our scenario, we introduce a new term called “Activity Zone” which is used to represent intensity range of a specific activity. For this purpose, we take advantage of built-in accelerometer sensor, and for training purposes, an external HR device. Details about sensors are given in chapter 3.3.1.

An overview of the concepts used in our scenario is given above. Now, the following subsection will provide the scenario under the lights of concepts described above.

## 2.1 Sedentary Lifestyle

In our scenario, we monitor a person who has a sedentary lifestyle involving little exercise, and spending a lot of time consuming little energy without being active enough. More details about our focus on sedentary people are provided in Section 2.3. Given that, as a result of sedentary lifestyle, Sam is diagnosed with obesity which is the condition that occurs when the amount of calories consumed exceeds the amount of calories expended over a long period of time. Excess calories are stored as fat in the body, and with long-term caloric excess, an individual eventually becomes obese. Exercising regularly and eating a healthy diet are effective ways of combating obesity [10]. Sam’s doctor strongly recommends that various kinds of activity should be performed to increase energy expenditure and a healthy diet programme shall be followed by the patient in order to combat obesity and inactivity. While it is Sam’s responsibility to follow the diet programme, the doctor decides to keep track of activity level of Sam. For example, Sam is recommended to use stairs instead of using elevator or bicycling instead of taking a bus when going to work.



As the doctor instructs, before allowing Sam to leave the clinic, he undergoes a training program by installing the application “zonEstimator (ZE)” to his smart phone and wearing a HR sensor. The application that is installed in his smart phone is started to take the training mode first. This phase is called “learning phase” which includes a simultaneous recording of an external HR sensor and built-in accelerometer sensor of the smart phone. The user is asked to make sure that Bluetooth connection in his smart phone is enabled and HR device is on running properly. The training phase takes a predetermined period of time (e.g. 5 minutes for each activity) in which the patient walks and runs respectively at slow and fast paces. It basically takes approximately 25 minutes (including waiting time for logging and interpreting the results after each activity) to conclude the training mode. Sam gets this phase done with the supervision of the doctor while the accelerometer sensor data values get logged with HR values. After successful completion of training mode, the user takes HR sensor off, carries only his smart phone, and runs the application on normal mode to estimate his activity zones.

The purpose of using an HR sensor is to collect personal real heart rate sensor data from the patient and define activity HR ranges for each activity for future purposes. The CA monitoring system is expected to provide isolated HR zones for each intensity levels meaning that activity zones do not intersect with each other in terms of HR values. For instance, the interval of BPM values for light-intensity activity like casual walking is presumed to be distinct from the interval for moderate-intensity endurance PA like Nordic walking. Likewise, we expect the same distinctive results for the sensor data coming from the smart-phone for the sake of accuracy. This will be used to form a ground truth for future purposes and serve as a reference for us to observe the correlation between HR sensor and smart phone sensors. Assumptions made for ranges will be evaluated later in the paper.

The doctor states that Sam needs to revisit the clinic next month for another consultation and to review the progress of his. The task for Sam is to perform a vigorous-intensity PA for a minimum of 30 minutes for three days a week. He continues his daily life but with some types of vigorous level exercises such as jogging. Meanwhile, he carries his smart-phone with himself and the activity level monitoring application that he has installed runs constantly. The intensity of the user’s activity is observed by the mobile phone. The application enables both the patient and the doctor to follow the patient’s progress of activity level, and allows for direct feedback in form of automated responses from the phone.

Sam can keep track of his progress on a daily basis by the direct feedback given by the application. Even in the next consultation, the logged data and results provide more information for the doctor to give further suggestions. The doctor decides if Sam has performed a considerable amount of activity rather than his old sedentary lifestyle. The doctor observes that Sam has noted an upward trend in his performance. Sam thinks that it was difficult to get used to completing 30 minutes of exercise each day and it was frustrating for him to see poor results in the early weeks of the process. However, he has got used to completing his task by running at least 30 min a day and he thinks that it is just a beginning of a new life style which will motivate him to leave the sedentary life style behind for good and live healthily.

The scenario mentioned earlier is used as a reference for defining the requirements of our monitoring system in order to determine an activity level of a person. Before providing these “Requirements”, first we provide the use cases in our scenario.

## 2.2 Use Case

Use cases are given as follows considering the scenario given in the previous subsection. They are used to represent main functionalities of the application by defining the interactions between the end user and the system. In our scenario we have three actors; the end user, zonEstimator Graphical User Interface (ZE-GUI), and zonEstimator Service (ZE-Service). The end user is the person who uses the application ZE. ZE-GUI represents the interface of the application letting the user interact with the system through graphical icons and indicators, while ZE-Service stands for the component that manages the operations, calculations, and analyses in the background.

We provide the main functionalities in two lists as given below;

**End user:**

1. Start the application
2. Click the “training mode” button if it is the first time
3. Click the “GO” button to start training mode
4. Start the application mode if the training mode has been completed before
5. Run the application
6. View history results
7. Quit the application

### Activity Zone Estimator Service:

8. Start Learning Phase
9. Stop Learning Phase
10. Start Application Mode

We provide the following use case tables in Figure 1 and Figure 2. Each table explains details of a use case. The rest of the use case tables are given in the Appendix A.

<b>Use Case ID:</b>	[1]
<b>Use Case Name:</b>	Start the application
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. End-user clicks on the application icon</li> <li>2. system-GUI starts</li> <li>3. system-Service offers two options; training mode and start mode.</li> </ol>
<b>Trigger:</b>	The user decides to run the application.
<b>Preconditions:</b>	The application "ZoneEstimator" has been installed successfully.
<b>Post-conditions:</b>	The user selects either "Training mode" or "Start mode"
<b>Normal Flow:</b>	ZE-GUI and ZE-SERVICE started
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	The application stops working unexpectedly due to a system failure or device failure
<b>Special Requirements:</b>	N/A
<b>Assumptions:</b>	N/A
<b>Notes and Issues:</b>	N/A

Figure 1: Use case : Start the application

<b>Use Case ID:</b>	[2]
<b>Use Case Name:</b>	Start the training mode
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. End-user clicks the training mode button</li> <li>2. system-GUI opens a new window showing the status and measurement values of sensors</li> </ol>
<b>Trigger:</b>	The end user needs to accomplish the training phase.
<b>Preconditions:</b>	N/A
<b>Post-conditions:</b>	N/A
<b>Normal Flow:</b>	ZE-GUI started
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	The application stops working unexpectedly due to a system failure or device failure
<b>Special Requirements:</b>	N/A
<b>Assumptions:</b>	User did not complete the training phase before.
<b>Notes and Issues:</b>	N/A

Figure 2: Use case : Start the training mode

This section covered the main functionalities of the system as well as the interactions between the actors. These functionalities will be covered in Section 6 in detailed by explaining what technologies are used to complete

<b>Use Case ID:</b>	[3]
<b>Use Case Name:</b>	Run the training mode
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. End-user clicks the GO button to start the training phase</li> <li>2. ZE-GUI displays a warning if the settings are not correct (ex: "zephyr button" is on, but no Bluetooth connection with the external device is available)</li> <li>3. ZE-Service makes the phone vibrate to notify the user that the training phase started.</li> <li>4. After 5 minutes, the phone vibrates again to notify that training for walking activity has finished.</li> <li>5. ZE-Service analyses the collected sensor data and makes calculations to create ranges for the current activity type.</li> <li>6. ZE-Service saves the ranges into a file.</li> <li>7. The user is notified to get ready for running.</li> <li>8. End-user clicks the GO button for the activity of running this time.</li> <li>9. The steps from 1 to 6 are repeated for running</li> <li>10. When training phase is over, ZE-GUI redirects end-user to the HOME page.</li> </ol>
<b>Trigger:</b>	The end user has not got the training phase before and he needs to accomplish the training phase.
<b>Preconditions:</b>	Accelerometer sensor of the smart phone and external heart rate sensor shall be working fine.
<b>Post-conditions:</b>	Activity zones are seamlessly defined and saved into the corresponding files.
<b>Normal Flow:</b>	ZE-Service expects the end-user to walk first and starts listening to sensor values and logged them for 5 minutes. Afterwards ZE-Service repeats the same procedure for the activity "Running".
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	<ul style="list-style-type: none"> <li>- The application stops working unexpectedly due to a system failure or device failure</li> <li>- There is a problem with saving the results due to overload or memory size.</li> </ul>
<b>Special Requirements:</b>	<ul style="list-style-type: none"> <li>• Heart rate sensor shall be worn and on.</li> </ul>
<b>Assumptions:</b>	<ul style="list-style-type: none"> <li>- User takes actions (walking and running) in a certain rhythm</li> <li>- The position of the phone is stable on the body.</li> </ul>
<b>Notes and Issues:</b>	N/A

Figure 3: Use case : Run the training mode

them. Next subsection provides information about focus groups to which our scenario could be applied.

### 2.3 Focus Groups

Public health is one of the main concerns of the European Union (EU). EU policy in this regard aims to endorse public health, take precautions against diseases and threats to health (including the factors that relate to the lifestyles of European citizens) by promoting research. According to “Europa Summaries of EU legislation”, physical inactivity is one of the biggest factors for premature death just as blood pressure, cholesterol, Body Mass Index (BMI), inadequate fruit and vegetable intake and alcohol abuse. PA is a matter of the utmost importance for people to learn to exercise on a daily basis. It is because of that PA is one of the cures to overcome common diseases and concerns of today such as obesity-related health issues and need of home care for ageing population in Europe and Asia. For that, there are many researches being conducted by EU. One of the researches relates to the development of a system for the ageing population who need of assistance at home [11]. This system is to help people to get rid of their sedentary lifestyle and to be more physically active, thus providing them with a less need of assistance at home.

In addition to that, “physical inactivity has been identified as the fourth leading risk factor for global mortality causing an estimated 3.2 million deaths (6% of deaths) globally” (World Health Organization - WHO). The main purpose of these studies is to provide a personal awareness of activity level and give incentives for people with sedentary lifestyle to be more physically active by encouraging opportunistic physical activities which mean replacing daily routine activities with more energy consuming activities like cycling instead of driving to work [12]. In this context, it is important to explain what we mean by being physically active and how to measure it .

The objective of this section is to explain why specifically sedentary people are our focus. Our discussion in this section is mainly based on an article “Circulation” published by the journal of the American Heart Rate Association [9]. As a matter of fact, the focus on “sedentary people” includes many other user groups as well when considering the health benefits of PA. Elderly people who are not physically active enough, obese people who need to change their lifestyle in a more active way, and even healthy adult people who have a sedentary lifestyle could be evaluated as sedentary people. Exer-

cise and PA have been shown to help maintain a healthy body weight, reduce stress, increase self-esteem and feelings of well-being, control blood pressure, and prevent heart disease and diabetes. Many adults, including those who wish to improve their personal fitness or further reduce their risk for premature chronic health conditions and mortality related to physical inactivity, should exceed the minimum recommended amounts of PA. To promote and maintain health, all healthy adults aged 18 to 65 yr need moderate-intensity aerobic (endurance) PA for a minimum of 30 minutes on five days each week or vigorous-intensity aerobic PA for a minimum of 20 min on three days each week.

The reason why we have chosen sedentary people as our focus is because of the health benefits that they are deprived of due to their lifestyle. Exceeding the minimum recommendation further reduces the risk of inactivity-related chronic disease. Because of the dose-response relation between PA and health, people who wish to further improve their personal fitness, reduce their risk for chronic diseases and disabilities, or prevent unhealthy weight gain may make positive contribution to their health by exceeding the minimum recommended amounts of PA.

To recap, sedentary people are our focus because of health related issues which have a direct relation with sedentary lifestyle. The outcomes of this paper and the developments done in the study may allow both the sedentary person and the doctor to follow the patient's progress of activity level in daily life without carrying an external sensor, and allow for direct feedback both in form of automated responses from the phone, but also from responses from the doctor or the physiotherapist. Though our focus is on sedentary lifestyles, our concept can be applied to cover other user groups as well. As an example, people who try to make a physical recovery after an accident might also relate to our concept.

By this way, an incentive might be created for the people with low activity levels by allowing them to see their progress.

This section provided the scenario the use cases, which are used to identify potential technologies and exemplify our monitoring system in order to determine an activity level of a person. Next section provides the design of the application planned before the implementation phase. We will now elaborate on the requirements, functional and non-functional blocks and key technologies.

## 3 Design

This section gives the details of design parameters derived from the scenario given before. It includes functional and non-functional requirements, and provides the functional blocks that explains the data flow starting from the end-user, going through mobile sensors, raw data, calibration, feedback and finishing the process by the user.

### 3.1 Requirements

The purpose of this section is to provide an insight of the requirements of our monitoring system. We will describe the requirements for measuring sufficient movement of a person. One of the main requirements of our activity level monitoring system is “Context” which has no standardized description and definition as stated by Christoph et al. [13]. Authors use their own definitions for context in their researches since it is difficult to elucidate the definition of context. However the term “context” in this paper, is meant to refer to the description given by Lane et al. [14] which states that “Context is any information that can be used to characterize the situation of an entity which could be a person, place, or object that is considered relevant to the interaction between a user and application, including the user and applications themselves”. In the light of this definition, we are able to easily point out the term “context” for our scenario. The scenario “Sedentary Lifestyle” presented in the previous section could be taken as an example in which the patient, his activity, smart phone sensors and monitoring application are the entities. Each entity characterizes the user’s situation which implies that these entities are the context of our scenario. Even though there are different types of context such as location, activity, time, and other types, our focus is activity context since we are out after determining the activity dose of the user.

The context that we focus on in our study is activity context, and his health parameter, HR measurement values. Activity context is about the activities that the user performs such as walking, running, eating, sleeping, reading and so on. However in our study, we mainly focus on physical activities that are considered as exercise such as Nordic walking or running which could be specified by degrees from low intensity (walking) to high intensity (running). The intensity level of an activity that a user performs enables us

to estimate the “activity zone” of a user which is a new terminology that we introduce in our study. Activity zone (AZ) describes how active the user is regardless of the type of activity, indicating that a higher activity zone represents a more active user. Endomondo, a fitness tracking mobile application presents a concept of HR zone (Figure 4) to the users by using an external device calculating energy expenditure and estimating the intensity of the activity. Similarly, we are out after ending up with such information for the user but with using no external device at all for the application mode. We will see how good smart phone could be for such monitoring. Regardless of the type of the activity, we introduce three AZs of low, moderate and high intensity levels. It is also important to note that in connection with his HR values, the way the activity is performed by a specific person will determine if the person exercises in a low, medium or high activity zone. In our study, zones are represented with different colours inspired by the concept of traffic lights. Red light represents low activity zone, while yellow is for medium and green is for high activity zone. More information regarding these colours are provided in the following subsection.

To provide information about user’s activity context, we could benefit from different types of sensors. Sensors can be evaluated in two categories; built-in smart phone sensors and external sensors. Today’s smart phone devices come with different types of sensors to provide new features and services to end-users. Accelerometer, gyroscope, GPS, light, and proximity sensors are some of the built-in sensors available in smart phones. Besides that there are also external sensors available that could be integrated into context detection systems. However context-awareness based on a variety of sensors is not our focus in this study, and might be covered in our future work. Sensor technology is elaborately covered in Section 4. In our study, we use only accelerometer sensor of the smart phone for activity context detection, and we benefit from an external HR sensor only for the purpose of creating a correlation with the acceleration values of the smart phone. By taking that correlation as a ground truth, without depending on an external device, we aim to be able to estimate the activity zone of a person carrying only a smart phone.

Furthermore it is quite important to stress that creating or improving a method for activity detection is not our focus. For meeting our need of activity detection, we took the methods of a CA application as our reference, which will be touched upon in Section 6. In our system, we are only able to detect if the user is walking or running at different paces. Thanks to the



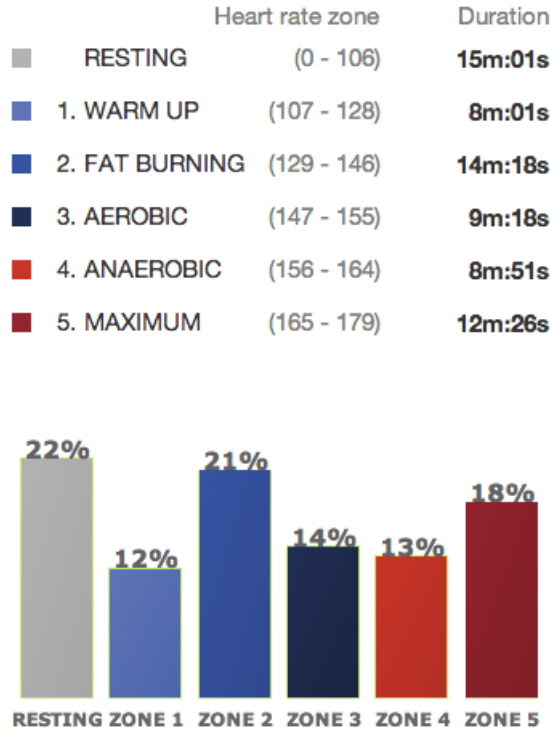


Figure 4: A screen-shot from Endomondo, a fitness tracking mobile application

correlation created in the training phase, we intend to know what HR zone corresponds to what activity type.

We will now elaborate on the requirements for our system in two categories; functional and non-functional requirements. Functional requirements correspond to system behaviours (e.g. collecting sensor data) whereas non-functional requirements are related to characteristics of the system (e.g. low battery usage).

### 3.1.1 Functional Requirements

Functional requirements stand for the main behaviours of the system. In this chapter we will briefly describe three main behaviours. For ZE, we have the

following functional requirements;

- **Create correlation (Training Mode)**
- **Show current activity zone on a daily basis (Application Mode)**
- **Show history (Report Mode)**

ZE requires a pre-phase for the application to run, which is called the **Training mode** in which ZE collects the results of accelerometer and external HR sensors of the mobile phone. As a result of training mode, **correlation** between HR values and acceleration values is created.

When application is on the **Run mode**, ZE performs the signal analysis in real-time by the help of the correlation created formerly in the training mode. It shows **the current activity zone** of the user, and records the results continuously into the log files for later purposes like reporting. Real time results are shown by the analysis of the accumulation of results in the current day. The mostly taken activity during a day is considered as the current activity of the user unless the user takes an at least 30 minutes of running activity, which means the current activity zone turned into green and will not change until ZE restarts for the next day.



Figure 5: Traffic Light concept for the representation of activity zones

In ZE, there are four categories indicating an activity zone; sedentary zone (e.g. sitting), low zone (low intensity walking around 3 - 3.5 km/h), medium zone (high intensity walking and low intensity running with average speed of 5.5 km/h), and high zone (high intensity running with average speed

of 8.5 km/h). ZE uses the principle of traffic light model with four colors; red, orange, light green and dark green. In our context, as demonstrated in Figure 5, red light represents sedentary zone, orange represents low zone, light green represents the moderate zone, and dark green represents the high activity zone. These zones are correlated with the previously measured HR measurements of the user and their corresponding acceleration values which were analysed during the training phase.

**Showing history** is another function of the system's and it enables user to check his history results of last seven days. ZE provides a couple of reports showing the past activity zone results of the user. The details of the behaviours described above will be given in Section 3.2 Functional building blocks.

### 3.1.2 Non-Functional Requirements

Non-functional requirements relate to performance characteristics of the system. Such requirements of ZE that we will cover in this chapter are as follows;

- **Usability** : ZE shall be defined for minimum complexity, meaning that it shall be simply enough for user to only open the application, follow some instructions, get the training done, and then use it.
- **Real-time estimation** : ZE shall provide a real-time estimation of the current activity zone of the user.
- **Accuracy** : Our main focus is to identify activities within a certain activity level meaning moderate as compared to sitting still. Thus, we are dealing with an activity indicator and an estimation of the activity zone. While other systems focus on activity detection of several activities, our system uses activity detection to get a good guess for the activity zone. The accuracy of ZE is evaluated in Section 7.
- **Low battery use** : Energy consumption is a challenge for smart phones due to their battery capabilities. Though it is not a focus of this thesis, we will evaluate the battery consumption of ZE in Section 7.
- **Run in Background** : ZE can run in the background while user starts another application.

- **Minimal storage** : Depending on the kind of operation, ZE might provide the log of all acceleration values. However, our goal is to only monitor the activity zone and only give a reference of that activity zone. Activity zone logging shall be performed text-based on the phone, thus ZE shall not require big storage capacity and writing huge amounts of data to the smart phone. Our design suggests not to store actual accelerometer data, but only results of the activity and the activity zone. Results of that are going to be discussed in the Evaluation section.

We have described the functional and non functional characteristics of ZE in this chapter. Now we will suggest the graphical interface of ZE by providing its main screens.

### 3.1.3 User interface (GUI)

In order to make the application easy to use, we will limit the functionality and just show the necessary information to the user. Thus, we are going to concentrate ourselves on four main screens in ZE; the **Home screen**, the **Training screen**, the **Application screen**, and the **History screen**. The **Home screen** enables the end user to go to any screen and quit the application (Figure 6). There are three buttons on the **Home screen** that can lead the user to any of screens described below.

The **Training screen** is to conduct training phase. The end-user clicks to the **GO button** after he makes sure that he wears the external HR sensor properly and puts his smart phone as expected. The HR measurements and acceleration values of the mobile phone are shown by the interface in this screen.

The **Application screen** represents the live monitoring by providing a color for each activity zone. The color could be red, orange, light green, and dark green regarding the current zone of the user. For instance, if the user has already performed a moderate activity (High intensity walking or Low intensity Running) for at least 30 minutes, he gets in the green zone which means he has completed the expected amount of daily activity.

The **History screen** provides information about the results of last seven days without the current day.

Similar design suggestions have been developed for the other screens. Implementation results of these ones are presented in Appendix B.

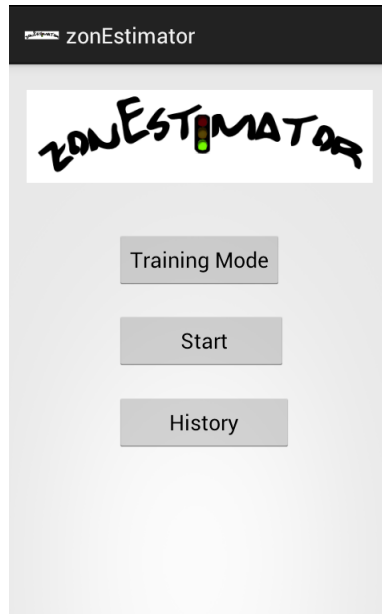


Figure 6: Home screen of ZE

## 3.2 Functional Building Blocks

This section provides and explains the functional data flow of the operations performed during a simple process of activity zone estimation. A conceptual framework for such mobile activity level monitoring is given (Figure 7). We created our functional data flow considering this conceptual framework starting from getting data from sensors, processing the signal, and transferring information to the application.

The functional building blocks for ZE are composed of three main blocks; the external block including Data storage, Built-in sensors and External Sensor. The GUI block manages all the items, buttons, components, warnings and information displayed on the screen. It also manages the interaction with the service block. The service block stands for the component that manages the operations, calculations, and analyses of the signal coming from the sensor block. It manages all information sent to the GUI block. We will now explain each functional block with the help of the data flow demonstrated in Figure 8.

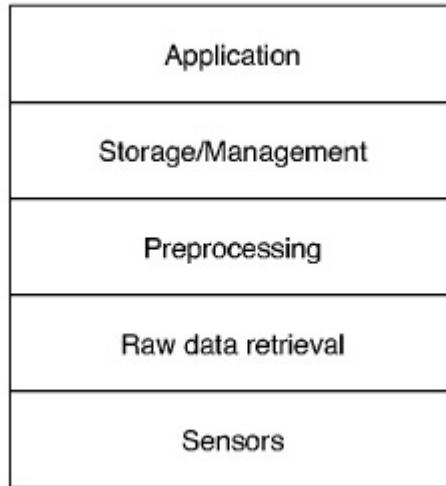


Figure 7: Conceptual Framework for Mobile Activity Level Monitoring [1]

### 3.2.1 External Blocks

In our concept, the external block includes both blocks provided by the mobile phone and blocks used externally (e.g. an external HR device).

#### 3.2.1.1 Built-in sensors

This block is in charge of managing the sensors available in the smart phone such as accelerometer, gyroscope, GPS and so on. In our case, we only benefit from the accelerometer sensor of the mobile phone.

Accelerometer sensor is being listened to and monitored by this method. Each time the sensor senses a new value, it is reported at a frequency defined by the Service block (3) and the system invokes this method. This method, eventually, returns a `sensorEvent` object that includes the following information; three physical axes (x, y and z) and time stamp (2).

#### 3.2.1.2 Data Storage

This block takes care of the logging and storing operations of the results (5) into a specific folder created in the Secure Digital Memory Card (SD) of the mobile phone.

### 3.2.1.3 External Sensor

This block manages the communication with external HR sensor. It listens to the external device and presents the incoming value to the Signal Analysis block (1).

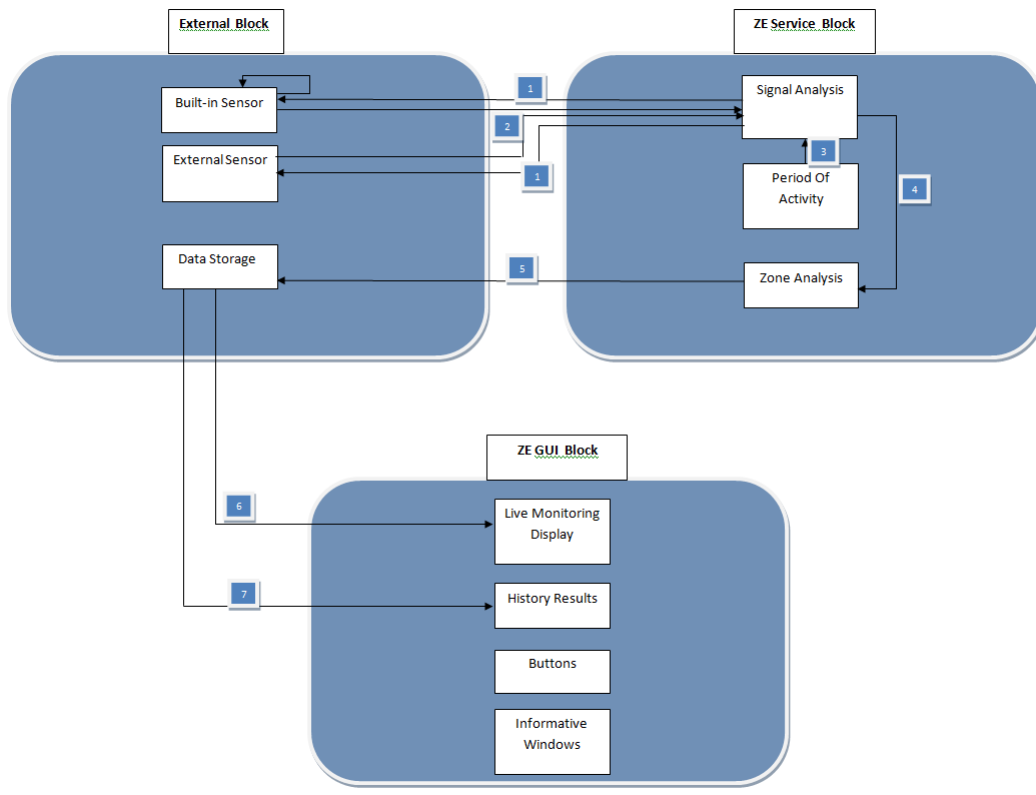


Figure 8: Functional Building Blocks

### 3.2.2 ZE Service

It is the main functional block that manages the signal analyses and operates the activity zone estimation. ZE Service encompasses the following functionalities;

### **3.2.2.1 Signal Analysis**

It takes care of the values retrieved from the built-in sensor and external sensor blocks (1,2). It analyses and puts them in order.

### **3.2.2.2 Period of Activity**

It is for monitoring the person on a daily basis. In order for ZE service to provide the current AZ of the person on real time, the current activity type is detected every four seconds and the data storage block records the results. This period lasts for 24 hours and ZE Service is notified to be restarted at midnight. When 24 hours of period ends, data storage block is informed to record the daily result into the related storage folder. A new period starts over for the new day.

### **3.2.2.3 Zone Analysis(with the help of HR sensor)**

It is conducted by the correlation, and the activity ranges created in the training mode. Each time when ALE service gets to detect the AZ of the person, it contacts with the data storage block (5) in order to compare the incoming values with the predetermined ranges (4). By checking the correlation this way, ZE service determines the activity zone of the person.

## **3.2.3 ZE GUI**

This functional block is in charge of handling all the interactions with the user. It is composed of the following sub functionalities

### **3.2.3.1 Buttons**

Buttons available in GUI of ZE enable user to move around the windows, start operations, and quit the application. The **Run button** in the training screen starts a communication with the ZE service in order to start listening to related sensors. The **Quit button** on the home screen allows the user to exit and close ZE.

### **3.2.3.2 Informative windows**

They are to warn or inform the user about what to do next in terms of completing the tasks.



### **3.2.3.3 Live monitoring display**

This block displays the estimated current activity zone of the person (6).

### **3.2.3.4 History Results**

They are shown in the history screen that provides a summary of activity zones of the user for the previous days (7).

This section presented the requirements and design parameters of ZE by explaining functional, non-functional requirements, and functional blocks that are necessary to understand the data flow starting from the very first operation like starting the application and to the last operation such as showing the current activity zone of the person. In the next section, we will be explaining key technologies, mainstream methods for activity level estimation, and real life applications in the area of activity level estimation.

## 4 Technology Review

In this section, we will have a review of the anatomy of activity context detection systems. We will first give a brief introduction to the area and then introduce key technologies for activity context detection systems.

In Section 1.1, we stated briefly that pervasive systems (also called ubiquitous systems) penetrated our lives and became an important part of our daily lives due to the reason that such systems enable users to focus on their tasks rather than technical issues. Systems created using laptops, smart phones, mobile sensors are examples of pervasive systems. CA systems are a part of pervasive systems as well. For instance, a software on a computer or an external device could operate depending on where the user is currently located, what the activity of the user is, or what the surroundings are. Today, especially improvements in wireless sensor technology and mobile systems caused to enormous demand in CA applications. In such CA systems, there are some technologies benefited from for some core functions such as data collection, context management, classification of information, reasoning (data analysis), and presentation of information. For the implementation of these functions, there are some technological elements common to most of the CA systems that we will present in the following section.

### 4.1 Data Acquisition

Acquisition of contextual information is important in the design of a CA systems because of the reason that it diagnoses the architectural style of the system. There are different ways of characterizing the user's context depending on what interest the application has. Either it is explicitly specified by the user, or implicitly acquired by monitoring the user [15]. The main purpose of such systems is to adapt to users seamlessly without increasing the load of the user, thus acquiring the context information automatically is what we are out after. In this respect, using sensors is key to collect such information without disturbing or preventing users from doing their tasks. In the next subsection, we will give a brief introduction to sensor technology and review different types of sensors for acquisition of contextual information [1].

### 4.1.1 Sensors

Sensor is a hardware, a device that is designed to acquire information from an object and convert it into an electrical signal [16]. This hardware is composed of three parts; the sensing element, signal processing, and a sensor interface. Sensors are commonly used to obtain context information in robotics and machine vision applications. They are becoming more affordable, easy to place on, and unobtrusive to wear with the advances such as size, power consumption, processing requirements, and cost-effective production [15]. Integration of multiple sensors in wearable computing systems, embedding sensors in a mobile device, and using sensors as independent devices are some of the relevant studies in the area of context awareness.

Although the traditional definition of sensor as given in the beginning of this subsection, the term “sensor” does not only mean a sensing hardware, it also refers to every data source which can provide contextual information. Matthias et al. [1] provides the classification of sensors in different groups; Physical sensors, virtual sensors, and logical sensors. We will now give a brief description for each group in the following subsections.

### 4.1.2 Physical Sensors

They are the most frequently used sensor types. They serve to sense different types of contexts such as light (e.g. colour sensor), visual context (e.g. camera), audio (e.g. microphones), motion (e.g. motion detectors), acceleration (e.g. accelerometer), location (e.g. GPS), touch (e.g. touch sensors implemented on mobile devices), temperature (e.g. thermometers), physical attributes (e.g. blood pressure), etc.

In this paper, we split physical sensors into two categories; built-in sensors and external sensors. For us, built-in sensors refer to the embedded sensors that are available in mobile devices, while external sensors mean the sensing devices located in out of the mobile device such as wearable sensors (e.g. an HR sensor).

Wearable or Body worn sensors have been used for different purposes such as on-line gait analysis, location tracking [17]. The main advantages of them are that they are easy to place on the body because they are lightweight, small and inexpensive. We can end up with very accurate CA systems by placing multiple sensors on the different parts of the body where exactly the context information needs to be gathered from. By this way, recognition

performance is increased and complex activities such as playing badminton or typing on a keyboard could be easily detected. However, there are still some issues need to be addressed. For instance, number of sensors may need to be increased depending on the complexity of the activities that the system aims to detect. In this sense, it would be too obtrusive for user to wear too many sensors.

Regarding the scope of our study which is about activity zones created by the help of correlation between the number of heart beats of the user and the acceleration of the smart phone, we need to have an external HR sensor providing us with HR measurements of the user. In that sense, we have found out that there are lots of products out in the market. Most of the products share similar characteristics as some have distinctive features. Polar, Zephyr, Runtastic, Garmin, Wahoo and Scosche Rhythm are some of the HR monitoring products that we picked to review in this context. Their common feature is that they provide accurate HR measurement for mobile applications. We compared them in Table 1 in terms of their compatibility with operating systems, the communication technology they support, and their battery life. Other than their common feature of monitoring HR, some provide extra functionalities such as calorie burn, speed, distance measurement, breathing rate monitoring, posture detection during the workout in real time in an accurate way. We will not go into so much detail regarding external HR monitoring devices due to the reason that what is important for us is to be able to measure user's HR in real time, which is provided by almost all of the external devices available in the market.

Product	OS	Communication Technology	Battery Power
 <p><b>Zephyr BioHarness 3</b></p>	Android	Bluetooth Classic	26 Hours per charge
 <p><b>Polar H7</b></p>	Apple iPhone 4S and more	Bluetooth 4.0	User replaceable battery (CR2025), and battery life up to 350 hours [18]
 <p><b>Runtastic Combo HR</b></p>	Android 4.3 , Samsung Galaxy S4 iPhone 5s,5c,5 and iPhone 4s	Bluetooth 4.0	The battery life is around 2.5 years given that it is used 1 hour per day.
 <p><b>RHYTHM Chest Strap</b></p>	Compatible with iPhone, iPad, and iPod	Bluetooth Classic	Rechargeable battery, avg. life 6 hours
 <p><b>WAHOO Blue HR Strap</b></p>	Bluetooth 4.0-enabled iOS device	Bluetooth 4.0	Replaceable 3 volt CR2032 coin cell battery is used and estimated to last about a year.
 <p><b>Garmin</b></p>	iPhone 3GS, 4, 4S iPad — iPod touch	ANT+ Adapter	Utilizes CR2032 battery, and user indicated that it can last about a year or more [19]

Table 1: Comparison of HR monitoring products [ [20], [21], [22], [23], [24], [25], [26]]

Built-in sensors are the sensors available in smart phones. Today, modern smart phones as a computing platform have been more powerful than ever with the introduction of new sensors in order to be able to acquire information about people and their environments. Let us provide a review of the sensors available in the most frequently sold smart phone brands in 2013; which are Apple iPhone5 and Samsung Galaxy S4 according to the study conducted by the research firm TrendForce [27]. Apple iPhone5 came up with a new finger print identity sensor in addition to the sensors available in the old

models such as camera, a digital compass, GPS, microphone, three-axis gyro, accelerometer, proximity sensor, ambient light sensor [28]. iPhone's main competitor Samsung does not have a finger print identity sensor in its last model smart phone, Galaxy S4, however it came up with different types of sensors that even iPhone has not got included yet. It has a gesture sensor, RGB light sensor, hall sensor, barometer, geomagnetic sensor, and a humidity sensor as demonstrated in Figure 9. Without going into too much details, the main point is that each built-in sensor of the mobile phone serves for a purpose and gather data about people and their environment. Studies show that smart phones are getting more powerful in terms of functionality with more and more sensors being embedded into phones [14]. They may be even replaced with external sensors in the future. For instance, there are some studies in which new types of sensors are embedded in standard mobile phone earphones in order to measure blood pressure, stated by Lane et al. [14]. In conclusion, the built-in sensors of the smart phones lead new applications to emerge and help systems to be less dependent on the external devices.

#### **4.1.3 Virtual Sensors**

Virtual sensors refer to data sources which collects context data from software applications or services. For instance, an application that checks employees' electronic calendars in order to estimate their day off and reorganize their working hours, or a service to determine a person's location by browsing a travel-booking system instead of using a tracking system (e.g GPS) could be considered as virtual sensors.

#### **4.1.4 Logical Sensors**

Logical sensors are used to solve higher or complicated tasks by using the combination of information sources, physical and virtual sensors, and involving additional information from databases. Given that a system's purpose is to detect an employee's current position. For that purpose, a logical sensor in this term could be created by analysing his login information at a PC and database mapping of devices to location information [1].

In this section, we have explained what mechanism is used for contextual data acquisition and described the classifications of sensor types. In our study, we chose to use physical sensors for the purpose of data acquisition as we think it is the best option for our study. The reason behind our decision



Figure 9: Built-in sensors of Samsung Galaxy S4 [29]

and the sensor types that we benefited from for our study will be discussed in Section 4.5, Preliminary Analysis. In the following section, we will elaborate on some protocols and technologies for data communication between devices for CA applications.

## 4.2 Sensor Communication Technologies

Data communication technologies could be evaluated in two groups; wire-line and wireless. However wireless systems are more appropriate for real life settings when it comes to health and fitness monitoring due to the way we perform our daily activities. Major disadvantage of today's wireless technologies

in comparison with wire-line technologies is their low power capabilities and vulnerability to eavesdropping [30]. In this section, we are going to cover data communication technologies that help built-in and external sensors transfer data between each other. Due to the fact that power consumption is a vital issue when it comes to employing sensors for applications, we will only give a brief description of the low power wireless technologies that are appropriate for communication between devices requiring low power consumption.



Figure 10: ANT+ Basics [31]

Want et al. [32] states that in the beginning, standards like **IEEE 802.11b (Wi-Fi)** were used to support local-area networking over wireless. Devices using mains power like laptops with large batteries or desktops could benefit from Wi-Fi for wireless connection without a problem of power consumption. However Wi-Fi in its original form, is an 11 Mbps network with power usage on the order of 500 mW, suggests Want et al. [32], which is not a good candidate for wireless communication of small devices with limited power.



Therefore, such devices having meagre power supplies needed a new wireless standard which consume less power. Then, **Bluetooth** standard was formed by Ericsson, Nokia and Intel companies in 1998, released as Bluetooth v1.0 in 1999, and became the IEEE standard in 2002.

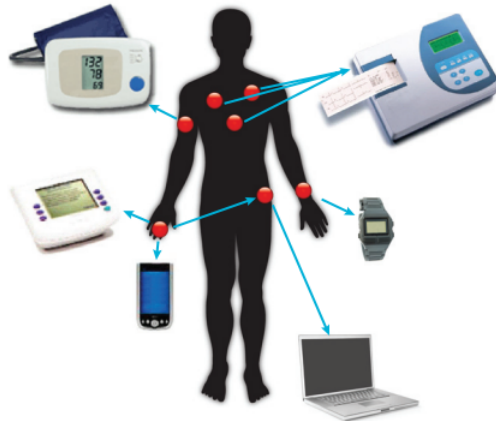


Figure 11: ZigBee Wireless Sensor Applications for Health, Wellness and Fitness [33]

However manufacturers producing low power devices such as HR monitors, and other kinds of small sensors did not use Bluetooth as expected. Bluetooth consumes tens of milliwatts, which makes it inappropriate for continuous long-term operation for devices with meager power supplies [30]. Instead of Bluetooth, alternate standards like ZigBee was preferred for wireless communication. Speaking of alternate standards, at this point we may briefly mention ZigBee, RF4CE, IrDA, and ANT as low power wireless technologies [32].

**ANT** is “a proven ultra-low power wireless protocol” [31] designed to provide communication between sports sensors and a display unit like a watch. Thanks to its technology of low level energy consumption, ANT devices are able to operate for years on a coin cell [34]. **ANT+** is introduced as a managed ANT network, which provides an open interoperability of data between ANT+ branded devices. As an example of that, by implementing the ANT+ HR monitor device profile, an ANT+ branded speedometer is able to show user’s HR by connecting to the HR monitor [31]. This ecosystem of interoperable devices is illustrated in Figure 10.

**ZigBee** wireless technology enables communication between simple and high-tech devices. It is considered as low power version for Wi-fi and targeted at smart meters, home automation and remote control systems that use low data rate communication [34]. ZigBee resembles Wi-Fi (802.11x) in terms of the way it works. The big difference is data rates and power demand. As we previously mentioned, Wi-Fi it is not designed for low power devices and it is used for data transmission at high rates. On the contrary, ZigBee technology is designed for the transmission of few bits each second.

There is an association called ZigBee Alliance formed by companies like Philips, Samsung, Siemens and some others. The goal of the association is to present a wireless technology into everyday devices by providing flexibility, mobility and ease of use. It also fosters monitoring applications (e.g. personal wellness monitoring as depicted in Figure 11) due to the fact that this technology enables low power communication between devices and services [33].

**IrDA**, Infrared Data Association, was built in 1993 in order to provide protocols low cost wireless technologies. Different types of products were produced with IrDA standard compliant ports since then [35]. Personal computers, personal digital assistants, digital cameras, mobile phones, printers are examples of devices with compliant ports. Widespread deployment has been achieved with IrDA. IrDA provides interoperable, inexpensive, wireless interaction between information appliances without an mediate [36].

**NFC**, Near Field Communication, was introduced to the field of wireless technology in 2004 by Sony, Philips, and Nokia. NFC promised to enable short-range wireless interaction (max. 20 cm) between electronics, mobile devices and PCs. The communication is simply made for two devices to be kept near to each other. NFC with the feature of low energy consumption is a better candidate for health monitoring applications because it is cheaper and less complex than Bluetooth and IrDA. NFC is used for health monitoring systems such as blood pressure monitors, blood glucose monitors, HR monitors as depicted in Figure 12 [30]. Such monitoring applications share their results with an NFC enabled mobile terminal and these results could be transferred to a web service via Internet.

With the release of Bluetooth v4.0 which is compatible with classic Bluetooth, a new concept called **Bluetooth Smart or Bluetooth Low Energy (LE)** is introduced. This new feature of low energy was improved in order to support the communication of power sensitive devices like wireless sensors (motion sensors, light detectors, HR sensors, pedometers). The main

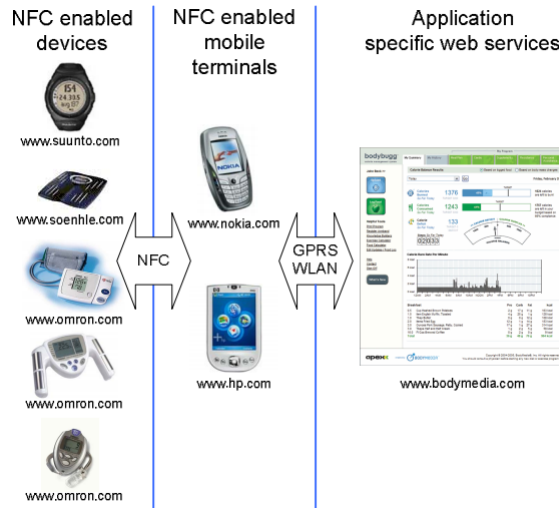


Figure 12: A data flow from an NFC enabled device to a web service [30]

purpose of Bluetooth LE was to be able to communicate with a wireless sensor spending 200 mAHr by using a laptop or a cell phone for at least one year [32]. Want states that Bluetooth LE protocol is limited to 200 kbps, which may sound a bit few in comparison with other protocols like Wi-Fi as an 11 Mbps. However, in fact it is sufficient for sensor applications that periodically transfer a small amount of data. Sending short messages, making connections to the device in a very fast way only when necessary are the keys of low energy consumption. This low energy principle of Bluetooth LE makes it possible for it to last ten times longer than a Classic Bluetooth Unit [37].

Both ad hoc protocols (e.g. Bluetooth) and wireless local area network protocols (e.g. 802.11x) are supported by the hardware that smart phones have [38]. Such protocols allow smart phones to connect external devices such as an external HR sensor in our study.

Each of the technology explained above aims to provide minimum energy consumption and each follows a different method. Minimum power consumption is based on employing sensors when only necessary, making connections with sensors as fast as possible (few ms) and avoiding to transmit long messages [37]. In this subsection, we have introduced low power wireless data communication technologies and mentioned their roles in health and fitness monitoring systems. In the following subsection, we will explain why choosing

mobile devices as a platform is a wise decision to make for context detection. In addition, we will give a brief explanation of different smart phone brands with different operating systems.

### 4.3 A Mobile Device as a platform

In this chapter, we will explain why mobile devices are preferred and getting more popular as a platform for context detection, and we will address some challenges regarding smart phones being as a sensor platform. In addition to that, we will compare different mobile phones available on the market.

As previously mentioned, today's smart phones are more than a communication device due to rich functionalities and expanded capabilities. They function as a small powerful computer with their fast processor, storage capacity, and the set of embedded sensors. To me, even before when we first met mobile phones, it was reasonable enough for us to carry our mobile phones all day long in our pockets just for communication with each other. Today, we feel like we cannot live without our smart phones because of the reason that they make our lives so much easier by providing us with so much facilities in our daily lives. We are able to use it as a camera, sound recorder, a navigator, media player, even as a wallet (e.g. the application called e-wallet). This all-in-one feature of smart-phones allows us to leave other devices behind and makes us more dependent on them.

A study commissioned by Nokia was analysed by a mobile technology consultant, Tomi Ahonen. He found out that users check their smart phones every six and a half minutes which mean in total "an average of 150 times of checking during a waking day of 16 hours" [39]. We can conclude from this study that the interaction between users and mobile phones is pretty high. Patel et al. [40] had an empirical investigation of the proximity of users to their mobile phones in order to figure out if the mobile phone is a good proxy for its owner's location. That study shows that users had their mobile phone at a very close proximity (at arm level) during an average of 58% of the time.

This nature of mobile phones presents a good opportunity to benefit from them for context detection without depending on an external device. It sounds better to eliminate the burden of carrying external devices on the body as long as the all-in-one concept is accurate enough for the same purpose. For instance, if a smart-phone in user's pocket is capable of detecting the user's activity given that battery consumption or other limitations are no concern, then why to use external accelerometer sensors put on different

parts of the body which is not a good way of motivation for the user [11]. To recall what we are out after in this study, we are trying to figure out how much we can get about a user's PA by using only his smart phone without depending on any external device. In this term, the fact that user tends to carry his smart phone with him all day and it is equipped with a precise and reliable accelerometer makes it a preferable platform in our study.

Today's market is full of manufacturers of mobile phone. The device itself is just a platform on what operating systems do the real work. It means that what creates the real difference between smart phones in terms of functionality is actually the type of the operating system. We will briefly describe the most common known five operating systems (OS); Research in Motion (RIM) Blackberry, Nokia Symbian, Microsoft Mobile, Apple IOS, and Google Android [41]. Due to the fact that the concept of our thesis which is about detecting the intensity of activities by built-in mobile sensors, our interest is basically in the period of time after when the first smart phone with built-in sensors is released in 2007, that is Apple's first iPhone. Before 2007, there were only RIM, Nokia and Microsoft on the market, which were not equipped with sensors available today.

Briefly our survey on operating systems in this part of paper is more about the time when Apple opened its Application Store in 2008. After Apple reported his success with App Store, other smart-phone and OS vendors have opened their own market. Regarding marketplaces, it is stated that Apple is the leader of the application store market while Google Android Market gains momentum and has the potential to compete with Apple [42]. Nokia OVI Store retains third place in the ranking, which is followed by Blackberry App World. Because of the reason that other app stores together are much more smaller than the size of Apple store, we will not be reviewing them. We will now briefly explain each OS vendors and also touch a bit on the health and fitness related applications available on each market.

#### **4.3.1 RIM**

Research In Motion introduced the Blackberry in 1999, which was the first smart phone on the market. It became the best seller afterwards. Its keyboard and unique functionalities such as emailing and agenda in comparison with other cell phone devices made the Blackberry widely adapted. It was even ranked by PC magazine as 14th most important gadget invented in the last 50 years [43].

Devices running BlackBerry 10 include an accelerometer, magnetometer, gyroscope, ambient light sensor, compass, proximity sensor [44]. RIM provides a market called BlackBerry World and an API for developers. When we searched the market for fitness and health tracking systems, we came across with few applications available which were either for calorie tracking or for fitness tracking. Most of these applications are actually targeted for other operating systems like Android and iOS, but made available later on for BlackBerry phones as well. Endomondo that we briefly mentioned in Section 3.1 could be an example of such applications. However, when scale it down with the applications that are built only for BlackBerry phones, there is not that much to talk about.

We will now give a brief description of the most popular sport related tracking systems made specially for BlackBerry mobile phones.

**CascaRun** is a tracking application specifically architected for BlackBerry 10. It provides functionalities for the users to monitor their outdoor activities like jogging, biking, hiking, skating, running, etc. As specified in the application's description, CascaRun is built in order to meet BlackBerry's high standards in terms of quality and performance. Regarding its functionalities, CascaRun is similar to Endomondo in some ways, which enables users to track any outdoor sport including duration, distance, speed and calories as shown in Figure 13 [45]. Even though CascaRun also supports HR monitoring by using a Bluetooth Smart (Low Energy) device (e.g. Zephyr HxM Smart BT 4.0), it does not provide any information regarding intensity of the activities as Endomondo does by splitting activity types into zones like warm up, fat burning, and so on as previously provided in Figure 4.

**Body Buddy** is a calorie tracker application that helps users to lose or maintain their weight. Users manually enter their meals into the application and the application calculates the total calories gained. Users can also automatically integrate their Nike++ runs into the application and the calories burned thorough the exercise are measured and reported to the user [46]. Calorie measurement could be an indication of intensity of the activity, yet the measurement is provided by Nike++ not by the application itself. Speaking of Nike+ at this point, we can briefly state that this low power wireless technology developed by Apple and Nike in order to provide wireless communication between Nike+ devices and digital products [47]. It is designed to measure users' daily activities and motivate people to be more active [34].

In summary, regarding RIM we can point out that there are not that much development done for the sake of fitness and activity tracking. Most

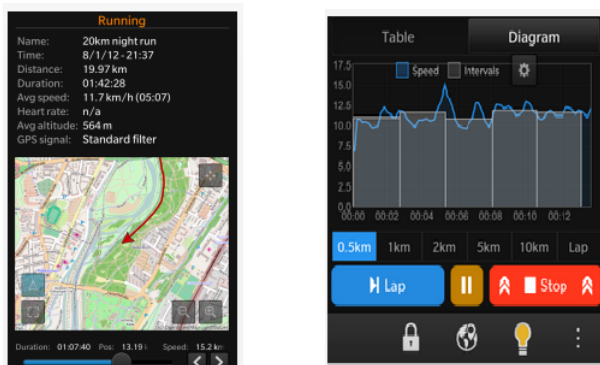


Figure 13: CascaRun Sports Tracker Screen-shots [45]

of the fitness applications that we found in Blackberry World are mainly developed for other operating systems such as Android and iOS. Besides that, some other popular fitness tracking systems are not even available in Blackberry World. This might be a result of the fact that BlackBerry has lost its popularity in comparison with its history like in 2000s.

#### 4.3.2 Symbian

Because of the reason that manufacturers such as Nokia, Ericsson, Panasonic, and Samsung agreed to collaborate to have a common operating system to run their devices, the Symbian OS was created. This collaboration allowed Symbian to have a dominant role in the market meaning that it hold a 65% of the market share. Despite the fact that Symbian aimed to have a vision of a single and collaboration effort, it started to fragment due to the willing of manufacturers, which is to give their own direction to the operating system. In 2008, all manufacturers except for Nokia gave up on Symbian and started to look for a new and innovative OS, which would be Android OS at that time.

Nokia provides a store called Ovi Store where developers upload their applications and customers download media, applications, etc. Besides that, there are some other independent Symbian stores as well such as My-Symbian.com, Symbian One, PocketGear, and GetJar [49]. We have found a couple of activity monitoring applications in these markets. Without going into details, we will just provide two examples of Symbian based monitoring systems as

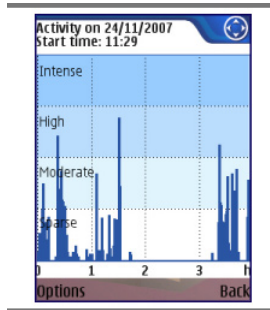


Figure 14: Nokia Activity Monitor [48]

follows;

**Nokia Activity Monitor** is an application developed for Nokia N95 device which has a built-in accelerometer sensor [48]. By the help of accelerometer sensor, the application is able to calculate total distance travelled, monitor the level of PA of the user during the day and produce activity reports as shown in Figure 14.

**Sports Tracker** is an application to motivate people to train better and live healthier. It was first built for Nokia Symbian mobile phones in 2004. The developers of the application states that Sports Tracker is the first application of its kind for mobile phones, and they are the category founder in the field [50]. Sports Tracker enables users to track and analyse their performance as given in Figure 15, and share their progress with friends. Users can also integrate an external HR device into the application in order to record HR measurements. However there is no activity detection mechanism using built-in sensors of the mobile phone and it does not provide any zone information regarding the intensity of the activity.

Speaking of Nokia, they also try to create new business opportunities in e-Health just like its competitors in this area. There is a Wellness and Healthcare team in Nokia Research Center, who aims to provide and maintain the quality that Nokia solutions and wellness devices, healthcare systems and other standards are able to be used together [51]. Besides that, Nokia has created a global competition called Nokia Sensing XChallenge. The purpose of the competition is to come up with a solution that takes advantage of the built-in sensors of the mobile phones and provides low cost health care monitoring in comparison with traditional laboratory tests. It is still an ongoing challenge and it will be resulted next year in 2014 [52].





Figure 15: Sports Tracker [50]

### 4.3.3 Microsoft

Microsoft also realized the fact that Blackberry was collecting the all credit in the mobile market in 2000s, thus reacted by releasing a device called Pocket PC 2000 with Microsoft's first OS, Windows Mobile. Windows marketplace was available for users to buy applications directly from their phones. New versions of Windows Mobile were announced by Microsoft until Windows Phone was released to the market in 2010. The main reason behind the decision of the change was to be able to compete with Android and iPhone smart phones [11].

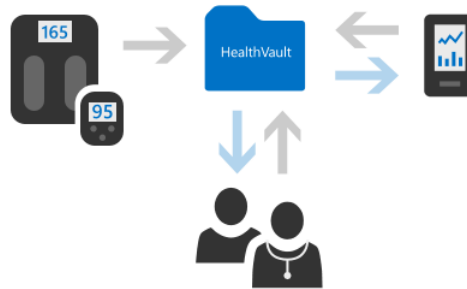


Figure 16: Microsoft's Health Vault [53]

Regarding health and fitness monitoring systems, Windows marketplace also include such applications with the same functionalities as we discussed for the previous brands. Apart from those third party applications, Microsoft presented a web-based platform, HealthVault in 2007 which is to share medical data for patients and health professionals. HealthVault functions as an

electronic repository and also a specialized search engine for health data [54]. Each individual has an account and can share their personal information with predefined users. The platform enables users to record their health and fitness data and upload to the platform (e.g. transferring data from a heart rate watch or a wireless body scale) as depicted in Figure 16. More detailed information regarding HealthVault is provided in its official website [53]. In 2013 Microsoft announced in an official website that they will launch Bing health and fitness application for devices that run Windows 8.1. It monitors and tracks user's workouts, diet and health by synchronizing to HealthVault platform for using personal information in a secure way. It still works as a part of the Windows 8.1 Preview meaning that it is still an ongoing process for Bing applications to get better in terms of functionality [55].

#### 4.3.4 IOS

Apple changed the course of the mobile phone technology by the release of iPhone, the first smart phone with sensors and with a multi touch screen. It made a huge success due to its original graphical user interface and easy to use environment. RIM and Symbian had to lose their market share as a productive tool after iPhone became a status symbol for people [43]. Apple store is made available where developers could sell their applications to the users and earn money without making any big producers a mediator. Moreover, easy to use SDK is provided for the development of applications. However, IOS is only for dedicated Apple products meaning that no other devices could run it.

As one of the biggest markets in terms of the number of users and developers, App Store houses many health and fitness related applications. Some of the popular fitness tracking applications are; Moves, Endomondo, Strava, and UP by Jawbone. Their common feature is to keep track of user's daily activity, encourage people to be more active by assigning new tasks and showing their activity reports. These applications make use of either the built-in sensors of iOS based mobile phones or some other external devices via Bluetooth such as Jawbone (a wristband that will be mentioned in Section 5.2.2.2) or combination of both sensors. We will not go into detail about each application because of the reason that we will review some real life applications in Section 5.2.

Unlike Microsoft's HealthVault and Google's Health platform that we will mention in the next section, we could not come across with any health related

framework developed by Apple. It seems for now that Apple does not plan to take such step in the area.

#### 4.3.5 Android

At the time when Apple got the control of the mobile market, Google Inc. created a group called Open Handset Alliance. They created the system Android and released it in 2009. The special thing about Android was that it is a Linux-based and open source system that could be used in different devices from different manufacturers. This feature of Android which is to be a completely open and a free platform let the manufacturers to get rid of the burden of dealing with a massive software development, thus enabling them to focus on hardware [43].

Google provides an SDK for developers and an on-line software store called Google Play (formerly Android Market) to share Android applications. As the biggest competitor of Apple's iOS, Google also has a lot of mobile developers and users. As an indication of that statement, it could be pointed out that more than 500,000 apps including health and fitness monitoring applications were available for Android in October 2011 [56]. Regarding health and fitness monitoring systems available for Android, we can briefly say that the applications explained in the previous sections have also Android versions benefiting from the built-in sensors of Android OS based smart phones. Some smart phone vendors also present their own health and fitness solutions. For instance Samsung presented a new concept called S Health that came up with the release of the product GALAXY S4 [57]. A brief description of this new concept is provided in 5.2.2.3.

Similar to Microsoft's HealthVault, Google Health Service was launched in order to enable people to access to their personal wellness information. However in 2011, Google announced to stop operating Google Health because of the reason that it did not have the expected impact [58].

In this chapter, we have explained why smart phones are a good platform for context detection. Plus, we gave a brief history of mobile phone operating systems and reviewed each market. Besides that, we reviewed what kind of health and fitness related innovations that the vendors are currently out after. The chosen operating system for our study is Android, we will highlight our decision to choose Android platform in detail in Section 4.5. In the following subsection, we are going to give a review of sensing frameworks that help developers to simplify the process and lessen the complexity of the

development of CA systems.

## 4.4 Sensing Frameworks

In this section, we will introduce some sensing frameworks for mobile CA systems, and explain why and when to use them. A software framework stands for “an ideal reuse of technique representing the core of software engineering reuse techniques” [5]. The main purpose of using frameworks is to support the development of CA applications by simplifying and overcoming applications’ development complexity. A framework could help to reduce development time, efforts, and cost. Plus, it provides less line-of-code and increases developer productivity. Hashim et al. [5] suggests that frameworks are classified according to their scope; infrastructure frameworks that relates to the development of system infrastructure like operating systems, hardware platforms, middle-ware integration frameworks that are used for the development of distributed systems like message-oriented middle-ware, and lastly enterprise application frameworks which are used to develop applications directly. We will not go into so much detail about each type of framework, or provide a comparison of them because of the reason that it is not our focus in this study. We will just give some examples of sensing frameworks available in the market.

**Energy Efficient Mobile Sensing System (EEMSS)** is a framework that is developed to address the battery power limitations of smart phones. The framework helps to use only necessary sensors of the mobile phone in an energy efficient way by managing them hierarchically for the purpose of recognition of user’s daily activities in real time. EEMSS saves battery power more than 75% and provides both good accuracy and low latency [59]. It has a special sensor management mechanism that decides what sensors are needed to monitor so that it turns on and shuts down a specific group of sensors based on the user’s current state.

**FUNF Open Sensing Framework** created by the MIT Media Lab, which is “an android based extensible sensing and data processing framework for mobile devices, which provides an open source, reusable set of functionalities, enabling the collection, uploading and configuration of a wide range of data signals accessible via mobile phones” [60]. It promises developers to save time, provide encryption mechanism for sensitive data and help logging and uploading proprietary application data and generic phone sensor data. Figure 17 represents the properties of FUNF; data collection objects called



Figure 17: FUNF Open Sensing Framework

“Probes” (e.g. accelerometer, gyroscope, proximity sensors, etc.) are shown on the left side of the figure, which collect a specific type of information such as location information provided by GPS or call logs. The phone collects the data coming from the probes and stores it in an encrypted format. This collected data could be extracted from the phone in different ways. It could be extracted by either manually sending by e-mail, or automatically uploading the data to a server. Then the collected data could be analysed or given to a data store or an application for further purposes. The source code of FUNF framework is accessible by Google Code. The code is composed of an application that functions as a collector and a number of scripts for visualizing the data. The functionalities of FUNF could be integrated into other Android applications by an API.

There are many other mobile sensing frameworks which mainly aim to ease the development of mobile CA applications. They help developers to collect the sensory data from the mobile phone without exhausting resource utilization, and to minimize power consumption. By this way, developers could focus on other parts of the application instead of writing some complex code.

In this section, as well as a couple of examples, we explained why and

for what purposes the sensing frameworks could be used for sensor based CA applications. In the following subsection, we will explain if it is beneficial to use a sensing framework in our study.

## 4.5 Preliminary Analysis

We have explained what core functions and technological elements are common to most of the CA systems. Here we provide a preliminary analysis explaining our decisions on what product and technology we preferred using for our study of CA zone estimation.

We first provided data acquisition mechanisms which relate to sensor technologies in our study. In that regard, we have split sensors into three groups; physical, virtual and logical sensors. We benefit from only physical sensors (an HR sensor, and accelerometer sensor) for the sake of defining activity zones in our study. There are already lots of products and devices out in the market with similar and distinctive features. The goal of this study is to estimate activity zones of the user, not to evaluate the accuracy of smart phone based HR monitors. Plus, our main focus is on transferring the HR data of the person to our application, we ignored the rest of specifications that the products have. In this sense, we have picked the “assumed” top-of-the-art reference model, being Zephyr BioHarness 3 external HR monitoring device for our study. One of the reasons why we chose Zephyr over other HR monitoring devices is that it is compatible with Android smart phones and there is a software development kit (SDK) provided by the company, which provides libraries for developers to build up new Zephyr supported applications in an easy way. There is even a package of BioHarness API and an example Android Project which is available in the official website of the product in order for new starters to adapt to development of applications supporting Zephyr HR sensors [61]. There is no specific reason why we have chosen Android OS over others. iOS or other operating systems could also have been taken into consideration, but evaluating the OS type when it comes to mobile supported activity monitoring is not our focus in this study. However, it was a plus for us to use Android OS since the products we decide to benefit from in our study support Android OS.

We touched upon sensor communication technologies that are used for health and fitness monitoring systems. We stated that the most appropriate communication technologies for sensors would be the ones promising low energy consumption because of the reason that energy consumption is a

vital subject of today when it comes to employing sensors with low power capabilities. It is important to note that optimizing power consumption is not our focus, thus choosing the most appropriate wireless communication technology in terms of energy consumption is not our concern in this study. We consider this topic as our future work that will be mentioned in Section 8. In this sense, any communication technology could be used taking into consideration that what type of external HR sensor and smart phone will be used for our envisaged study. We decided to choose Bluetooth classic in order to provide communication between external Zephyr HR sensor and smart phone regardless of power consumption benefits of low energy communication technologies like ANT and Bluetooth LE.

Another topic we covered in this section is about using mobile phones as a platform for CA applications. We examined the role and activities of each OS vendor in regard to health and fitness related topics. Considering wider market acceptance in regard to the number of users and developers, we have picked Android and iOS operating systems as the strongest candidates for the development of ZE. The criteria for us while choosing an operating system was to be able to benefit from the built-in accelerometer sensor of the smart phone and to be capable of communicating with the external HR sensor via Bluetooth wireless technology. iOS could also be selected in our study, however we have selected to use Android based smart phones. Again it should be stated that the goal of our study is not to evaluate operating systems on account of their suitability to be a platform to create a CA application.

In my opinion, it is useful to benefit from sensing frameworks to facilitate the development of complex CA applications which provide extremely rich context information of the users by making use of some combinations of built-in sensors and consume so much power regarding the resource utilization. In our study, we did not think of integrating a sensing framework into our study since our application, ZE, is not a sophisticated CA application, meaning that there is only one built-in sensor in use for the purpose of detecting specific number of activity types. That's why we would not have got the advantages of such framework considering the scope of our study. However, a sensing framework could be advantageous considering future version of our application. We will discuss how it could help us improving our application in Section 8, Discussion and Future Work.

It is important to note that, using multiple sensors for context detection is a big hurdle for the limited battery capacity of the smart phone. An example is given by Wang et al. [59], Nokia N95 can support telephone

conversation for longer than ten hours, but their empirical results show that the battery would be completely drained within six hours if the GPS receiver is turned on. There is a trade-off between the accuracy of detection and battery consumption.

In our current scenario, we only benefit from the accelerometer sensor of the smart phone, however, we may think of using other built-in sensors when our scenario requires so. At this point, using a smart phone as a platform with limited battery is needed to carefully taken into consideration. We provide more information regarding battery consumption in the Evaluation part of the paper.

To sum up, we have selected Zephyr BioHarness 3 device as our external HR monitor sensor which is capable of connecting to Android Smart phone via Bluetooth technology. We have used two Android Smart phones in our study; Samsung S2 and LG G2, which comes with built-in sensors including accelerometer sensor which is the only sensor we plan to use in our envisaged study. Other than that, we have not considered using a sensing framework due to the reason that our CA application is not that complex to develop.

In the following section, we will elaborate on measurement methods used for activity monitoring systems, and how the intensity of an activity is calculated. Plus, we will provide a literature review, brief summary of ongoing developments, and a walk-through of real life applications.



## 5 Methods and Applications for Activity Monitoring

This section explains measurements that include both types of activities, intensity of these activities, and identification of the measure itself. Measure of activity is often expressed through metabolic equivalent task (MET), indirect calorimetry, and respiration chamber. A detailed literature review, examples of ongoing developments and a walk-through of selected applications will also be reviewed.

### 5.1 Calculation of the Intensity of Activity

According to WHO [62], “Physical activity is defined as any bodily movement produced by skeletal muscles that requires energy expenditure”. Energy expenditure in the definition is our key to differentiate activities from each other in terms of intensity. But the question is if there is a formula to calculate energy expenditure ?

Accurate quantification and assessment of the intensity of PA is very essential to determine how important a PA is for a specific health outcome and for the evaluation of the relationship between activity levels and health. For this purpose, there are different methods ranging from questionnaires to laboratory tests used by both medical personal and end users [11]. Method in this context means the way how we assess the intensity of a PA. As pointed out by Vanhees et al. [63], there are three main methods for observing the activity of a person. These methods are criterion methods, objective methods and subjective methods. All methods aim to assess PA but by following different procedures, which causes them to have advantages and disadvantages over each other. We will give a short introduction to all of these instruments in order to show the interrelation between them and to show how mobile phone based sensor measurements relate to parameters being estimated through other methods. In the following section, we will give a review of these assessment methods and explain their characteristics as well as compare them with the following criteria; feasibility, accuracy, expense, and scalability.

### **5.1.1 Subjective Methods**

Subjective or self-reported methods are the most commonly used, inexpensive and easy techniques to apply in large populations. Survey techniques are split into four categories: self-reported questionnaires, interviewer-assisted questionnaires, proxy-report questionnaires and diaries. Answers of the questions are subjective and this may lead to inaccuracy or bias in the assessments. Besides that, some factors such as social desirability, age, complexity of the questionnaire, seasonal variation, length of period surveyed may result in under and over estimation of PA. Subjective methods are good at assessing the PA level of a group but it is not advisable to apply for individual analysis [63].

### **5.1.2 Criterion Methods**

The term “criterion” stands for a parameter by which something can be assessed. Therefore in this context, criterion methods correspond the techniques by which we can assess physical activities. Now, we are going to introduce some criterion methods which are used for the assessment of physical activities.

#### **5.1.2.1 Direct observation**

Direct observation is a way of assessing PA by the observation of the motor activities. Experienced observers take charge in this kind of observation. They observe the activities of the subjects in their usual environment by watching or videotaping them and quantify the activities. The benefit of such observation is the access to contextual information [63]. This technique is mostly used for the observation of the activities of children for the reason that other methods such as pedometers or questionnaires which will be explained later are not applicable to this group [64]. The drawback of this technique is that applying this method is a very time consuming job and expensive in terms of data collection. Therefore it is not advisable for large-scale studies [63].

#### **5.1.2.2 The doubly labelled water method (DLW)**

DLW is one of the most accurate methods and can be applied in laboratory and field studies. In this method, “The people drink water laced with stable

isotopes of hydrogen and oxygen. The loss of these isotopes over time as assessed from saliva, urine, or blood provides an estimate of energy expenditure” [65]. The results retrieved via this method are accurate because of the reason that it measures the metabolic processes that are directly related to PA. On the other hand it has limitations in terms of the cost of production and analysis of isotopes [63].

### 5.1.2.3 Indirect calorimetry (IC)

IC is a method that is related to oxygen consumption and carbon-dioxide production. Energy expenditure (EE) is measured by a respiration chamber or a ventilated hood. This method is accurate but it is pretty expensive to apply. Another disadvantage of this method rather than expensiveness is its inability for a person to fit in a free-living situations [66].

Regarding oxygen consumption for the assessment of an activity, it is convenient to touch on a bit of Metabolic Equivalent of Task (MET) in this part of the paper. MET is defined by the medical research in order to compare the amount of effort needed for different types of activities. “MET is the ratio of work metabolic rate to a standard resting metabolic rate” [10]. “MET is only estimation but determined after realistic tests in laboratory” [11].

A coding scheme that classifies specific activities is provided by the Compendium of Physical Activities. We are able to categorize specific activities as light, moderate, and vigorous due to the MET value assigned to them as provided in Table 2.

It is well stated by Ainsworth [10] that MET classification is not developed for a precise estimation of energy cost but as an activity classification system. However it is possible to benefit from MET value for the estimation of activity level and calculation of calories burned during the activity. Byrne [67] conducted some studies and found out that there is a 20% of overestimation of the standard resting energy expenditure used by MET classification. In order to have precise results, Byrne proposed to adjust MET level for the differences between measured and estimated energy expenditure. By the equation proposed, it is possible to calculate the energy expenditure in kcal for a specific activity on condition that the parameters such as age, weight and height of a person are also known. Given that, we estimate the energy cost for a man with the following characteristics ;

**Age** 25 years old

<b>Physical Activity</b>	<b>MET</b>
<b><i>Light Intensity Activities</i></b>	0 to 3
Sleeping	0.9
Sitting quietly	1.0
Walking, less than (3.2 km/h)	2.0
<b><i>Moderate Intensity Activities</i></b>	3 to 6
Walking downstairs	2.5
Slow Swimming	4.5
Walking at a very brisk pace	5.0
<b><i>Vigorous Intensity Activities</i></b>	6 to 10
Slow Jogging	6.0
Jogging	7.0
Running, less than (10 km/h)	10.0

Table 2: MET per kind of activities

**Weight** 75 kg

**Height** 180 cm

**Activity** Jogging for 30 minutes

After calculating the adjusted MET value with age, weight, height, and RMR (Harris-Benedict equation) as proposed by Byrne, we can calculate the energy cost as follows (given that adjusted MET is 7.5 for the sake of the argument);

$$\text{MET-adjusted} * \text{hour} * \text{kg} = \text{kcal}$$

$$7.5(\text{MET-adjusted}) * 0.5 (30 \text{ minutes}) * 75(\text{kg}) = 281,25 \text{ kcal}$$

In summary, one MET is 3.5 ml/kg/min in terms of oxygen consumption. Because of the reason that more intensive activities require proportional increases in oxygen consumption, activities could be measured and compared on a standard scale thanks to METs. However, the adaptability of the body to PA is an important fact to take into account. It means that because of the fact that body adapts itself to make exercise easier, the same level of activity could affect people in a different way. A moderate intensity activity for a fit person could be running slowly, while it could be walking slowly for a sedentary person. In other words, MET values are easily affected by the user characteristics such as the physical condition or the genetic determinants of

the user [68]. In this term we could briefly state that using MET has a limitation in standardizing activity levels [66]. Despite this limitation, we might think of evaluating MET values in our future study.

The criterion methods require an in depth observation and knowledge of the person. Although they are the most objective methods, they are not practical to be applied on a large scale. We have described them in detail in this part of the paper, because they are often used as a standard for validation of the methods that we will describe next.

### **5.1.3 Objective Methods**

Objective methods are applied based on an external device delivering related information of the patient to the related observer mechanism. Unlike laboratory based methods like IC, objective methods are more feasible to apply on a patient wearing an external device in outdoor.

#### **5.1.3.1 Pedometer**

Pedometer is an instrument that assesses the movement of the person by counting the number of steps. Studies have shown that pedometer is a great motivator for people to be more active. It started to become popular in 1965 in Japan by the acceptance of a slogan which was promising wellness and prevention of diseases with 10000 steps per day.

There are different types of commercial pedometers such as mechanical ones and others on a 3D space [11]. Rather than number of steps, these pedometers have also been used to provide other information such as the amount of calories burned. Regarding the accuracy of pedometers, a study states that five models underestimated the steps by 25% while three overestimated by 45% among 13 different pedometer models compared and analysed [11]. Besides that, there is a 30% of overestimation in terms of energy expenditure when the results of indirect calorimetry are considered as standard. As a result, a pedometer is a nice tracking device, a feedback tool, and a good motivator for people to be more active. However they are incapable of providing accurate information about the intensity of the movement [63].

#### **5.1.3.2 Accelerometry**

Accelerometry is a method that utilizes uni-axial or multi-axial accelerometers to estimate energy expenditure [11]. It is a commonly used technique

in PA research, which try to detect activities with accelerometer sensors and calculate EE. Accelerometry provides movement intensity and more detailed analysis in different time frames in comparison with a pedometer. In the old studies when accelerometer was an external device, it was considered as an expensive method than using a pedometer. Furthermore, it could be stated based on the researches that accelerometer-based monitors are not a good indicator of EE while good at estimation of overall PA [63]. In addition to these drawbacks, technical problems such as limited battery and users' non-compliance like not wearing the device or positioning it incorrectly are other issues observed in the studies [64].

However, today the story is different than before with the pervasive systems that have already penetrated our lives. Especially smart phones that we carry with us along our daily life activities are full of built-in sensors including an accelerometer sensor. Moreover smart phones are capable of doing complex processing, that allow us to do real time analysis. Briefly, without the need of carrying a dedicated external device we are capable of doing an accurate measure of activity level. We will provide some examples of such activity monitoring applications using accelerometer sensors in Section 5.2.

### 5.1.3.3 Heart Rate Monitoring

It is another technique to assess PA. "Heart rate is an indication of the intensity of a relative stress that is placed upon the cardio-respiratory system during movement and is therefore an indirect measure of PA. This method is built upon the linear relationship between HR and oxygen consumption in the moderate to vigorous range of PA" [63]. There is an approach called FLEX HR that is to estimate EE from HR monitoring. HR monitoring can be applied for a long period of time, thus providing information about duration, frequency and intensity of the activity and even EE. However especially for light-intensity activities, what makes estimation of EE with heart rate monitoring difficult is the confounding factors such as caffeine, stress and body position. These factors cause to hindrance to understand if the increase in HR is caused by PA or the environment unless this kind of relationship of the subject is known. However HR monitoring is considered as an expensive technique for EE because of the fact that an individual calibration of HR and PA relationship is required [63]. Another drawback of hear rate monitoring is the time lag formed when measuring HR and monitoring the activity. Studies show that it takes 2 to 3 minutes for heart rate to reach a certain level as

representative of the activity being performed [66]. However, HR monitoring is a good instrument for the retrieval of objective information regarding the intensity of PA under controlled conditions.

To sum up, criterion methods like indirect calorimetry are the most accurate and reliable methods among other techniques for EE. However they are not applicable for daily life because they are expensive to conduct and limited to laboratory setting. Objective methods like pedometers and accelerometry have shown an accuracy as 90% for previously trained activity types while they are not good at it when it comes to monitoring complex activities. Heart rate monitoring as an objective method is lightweight and portable but not suited for low intensity PAs. Ultimately, questionnaires are the most commonly used techniques as they are very cheap and easy to apply on large samples. However, they should be validated by a criterion methods due to the reason that they depend on subject's answers and memory [63].

The main challenge of objective measures is the distinction between different types of activities, and as earlier pointed out, the challenge of equipment position and battery lifetime. Modern mobile phones have the capability of doing complex analysis thanks to multiplicity of sensors and reasonable battery lifetime given that the monitoring mechanism is optimised enough not to kill the battery. Using them for both controlling the type of activity, the position of the sensors, and the calculation of the PA is seen as the best solution for us. For that purpose, calibration is needed to adjust metabolic parameters and the measured sensor data retrieved from the mobile phone.

## 5.2 Real Life Applications

According to WHO, 60% of the worldwide population does not benefit from the health benefits of PA due to their sedentary life styles [69]. There has been many studies conducted in the field of activity level estimation with different mobile technologies. With the penetration of emerging technologies such as Bluetooth Smart and ANT, the number mobile sensing and fitness applications and the demand for them have increased. It was expected that the year, 2013, was to become an influential year due to \$800 million venture funding in the area. The number of mobile sensing health and fitness application downloads is 150 million, and an increase of 900% is expected for the next five years [70]. In this section, we give a review of modern researches conducted and applications developed in this area. Common purpose of such studies is to encourage and motivate people to take daily physical activities.

These kinds of applications provide incentives for users to be more active by enabling them to view activity reports and share the results with friends. The following sections provide examples of research indicating health promotion tools, talk briefly about available commercial products on the market, and then provide a short introduction for computer games encouraging PA.

### **5.2.1 Research deployments for Health Promotion Tools**

Health promotion tools address the problem of sedentary life style. Such tools aim to help people get rid of their sedentary life style and become more active by showing how active they are in their daily lives. There have been different research deployments that were built using mobile phones and external sensors, which aim to come up with a tool that help people to perform sufficient PA to maintain proper health, and now we will mention such health promotion tools developed by researchers. Examples of such health promotion tools are Shakra having the focus on activity level detection by signal strength, Houston focusing on stimulating people to increase their step counts and share the results with friends, Activity Level Estimator (ALE) that focuses on the categorization of activities by using a mobile phone and aims to help user to reach a dedicated activity level (e.g. 30 minutes of Jogging) by showing the user how much time he has spent on each activity, and Actitracker focusing on classifying user's physical activities and letting them see if they perform sufficient activities during the day.

#### **5.2.1.1 Shakra**

Shakra is a prototype application developed in 2007 that runs on the mobile phone, which could be considered as a health promotion tool. It basically keeps the track of the daily exercise activities of the user as given in Figure 18. It uses fluctuation in GSM signal strength to detect activity patterns, and also benefits from the changes in the visibility of GSM cells in order to infer if a user is still, walking or driving a car. The way the fluctuation of GSM signal works is similar to the signals of a traditional accelerometer. After detecting the user's activity, the application uses a look-up table to estimate the activity level. Shakra then calculates the daily activity level of the user and shares this result with others. The main goal is to stimulate adults to achieve 30 minutes of moderate activity five times per week [69].

A user study showed that Shakra's functionality of sharing results with



friends made a positive impact on the users. They were motivated to be more active in order get better results in the competition.

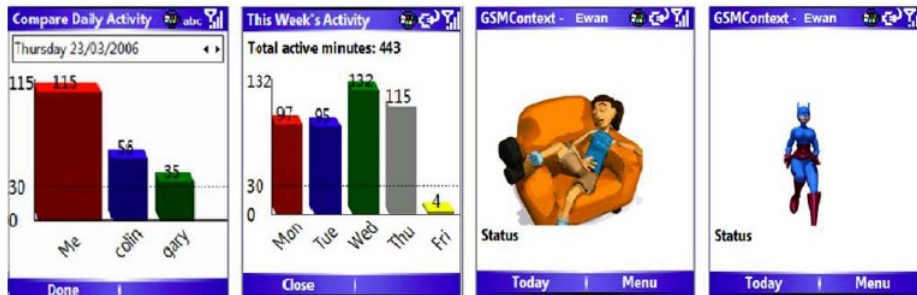


Figure 18: Screenshots of the prototype application, Shakra

Before putting a comment on this application, it should be recalled that the research deployment of Shakra was conducted by a traditional mobile phone not by a smart phone. That’s why, we can only give our opinion about how the method of fluctuation in GPS signal could be used in modern activity detection systems benefiting from the built-in sensors of the smart phone. This application is able to detect a very limited number of activity types; stationary, moving, and driving. There is no other types of sensors such as accelerometer sensor used in order to detect other activity types (e.g. moving but walking or running). That’s why, it might be reasonable to think that it is possible to differentiate accurately if the user is stationary or not by the method used in Shakra, but in terms of accuracy, employing only the GPS signal strength for detecting complex activity types is not applicable for today’s scenario. It can only be an assistant to detect complex activity types if it is reasonable to do so for the sake of some parameters such as accuracy and battery consumption that we will discuss later in this paper.

### 5.2.1.2 Houston and Chick Clique

These are prototype mobile phone applications which are composed of a pedometer and mobile phone [71]. A digital pedometer counts the number of steps and then end-user enters the results into the software everyday. Houston stimulates people to be more active by sharing their step counts with friends as in Figure 19.

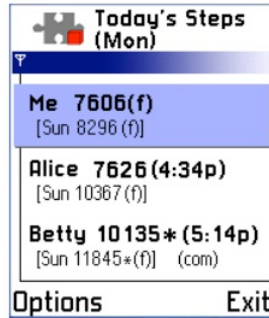


Figure 19: Main screen of Houston application

Similar to Houston there was another pedometer based project called “Laura” that aims to increase the steps of female adults. However, Laura works as a virtual exercise advisor that uses an animated conversational agent that uses social dialogue in order to encourage the users, while Houston has the peer sharing feature for that purpose [12].

Such applications using pedometer is only able to give an idea of the level of PA activeness in terms of step count, meaning that they cannot tell about the intensity of PAs. Houston, Chick Clique, and Laura aim to increase the total step count of the user and share the results with friends.

### 5.2.1.3 Activity Level Estimator (ALE)

ALE is an application developed by Jody et al. [11] for the research on the feasibility of using a mobile phone to detect user’s activity and calculate his energy expenditure. ALE classifies activity types in five categories; sedentary (standing, sitting, sleeping), very low (walking slowly), low (walking normally), moderate (walking fast), and vigorous (running). The user is able to view the amount of calories he has burnt and amount of time he spent for each activity type as in the screen-shot of ALE in Figure 20.

ALE detects the activity detection by the accelerometer and orientation sensor of the mobile phone, logs the details such as the duration of the activity and so on, and then calculates the energy expenditure. The amount of calories burnt is calculated by using two parameters; resting metabolic rate (RMR) and metabolic equivalent of task (MET). To get more information about how these parameters are used for energy expenditure, details could

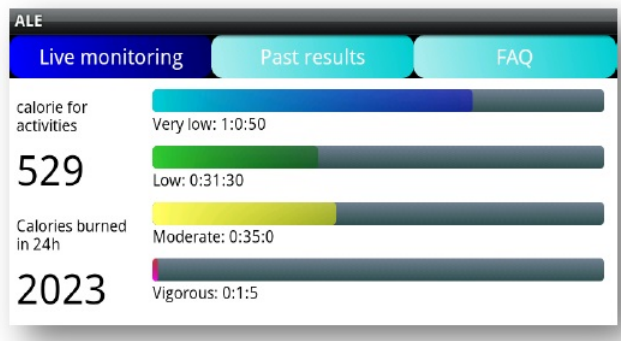


Figure 20: Live monitoring view from ALE

be found in [11]. The validation of the ALE application was conducted with a SenseWear product (briefly covered later in this chapter) and observed that the accuracy of ALE for moderate activities is with an average of 86%. During the comparison, some low level activities were not correctly classified using ALE. Our comment on this product would be that ALE is one of the most accurate mobile monitoring systems that can classify activities based on their intensity levels without using any external sensor. ALE made it possible by MET values created by the parameters asked from the user (e.g. age, weight), however we are out after if it is possible to tag health related data with built-in sensor data which is accelerometer in our study. At this point, we could point out that we benefit from the activity detection mechanism of ALE in order to detect activity types in our scenario. We will provide more information regarding this in Section 6.

#### 5.2.1.4 Actitracker

It is a sensor-based mobile activity recognition application developed by a research group in Fordham University. It utilizes the built-in sensors of the mobile phone for data collection, uses data analytic research from the WISDM lab (details given in 4.2.2) and classifies the amount of daily activities of the user (e.g. walking, sitting, etc.) [72]. The purpose of the application is to let end-users see if they perform sufficient physical activities to maintain proper health. It provides real time results and detailed activity history (Fig.8b).

Two different models are provided to run the application. The default option is the Universal model which could allow the user to run the appli-

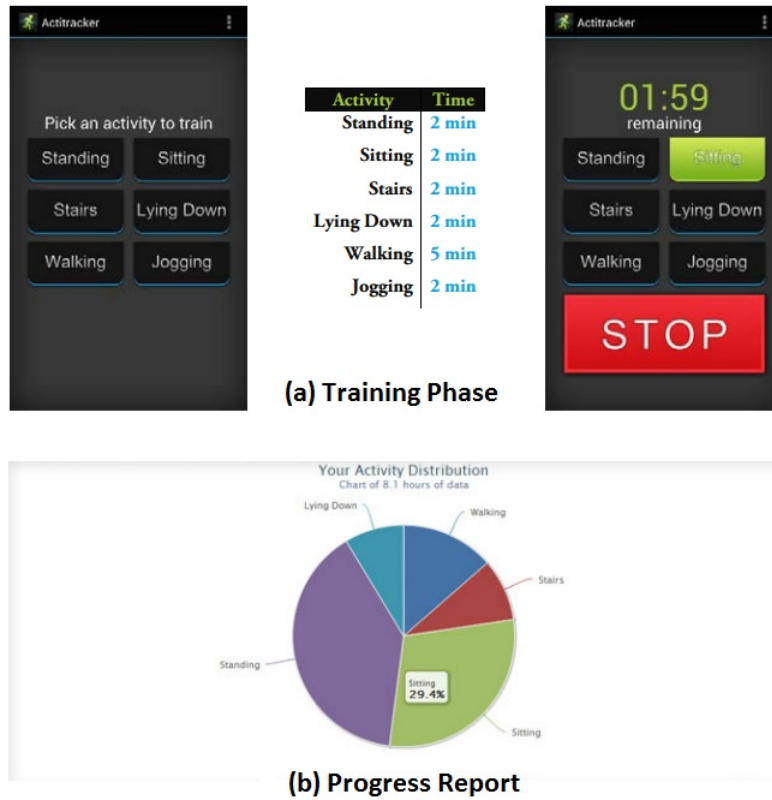


Figure 21: ActiTracker

cation without any training. Personal model, on the other hand, requires user to train (Fig.20 a) before running the application, which has better accuracy in comparison with the Universal model. The recommended position to place the mobile phone is the user’s pants’ pocket. Other places such as jacket pocket, purses, bags are not advised for the sake of the accuracy of the results. The application enables users to review their progress reports as demonstrated in Fig.20 b.

To sum up, we provide a comparison of the aforementioned health promotion applications in Table 3. Our evaluation criteria is defined based on the following parameters; “easy to use” parameter regarding the user interface of the application and if any external device to carry, “objective” parameter stands for if the application has met what is expected from it, “accuracy” parameter stands for the accuracy of results for the activity types that the ap-

plication can detect, “motivation” parameter means that if the application succeeded in creating an incentive for users to be more active, “intensity” parameter is to check if the application is able to differentiate the detected activity types based on their intensity levels.

The study of Shakra aimed to provide a lightweight application without any specialised external sensor, and achieved its objective by detecting a limited number of activities using the GPS signal of the phone. Houston and Chick Clique have achieved their objective of creating a motivation for users to get more active by enabling them to share their results with friends. ALE aimed to see the feasibility of using a mobile phone for activity detection and for the estimation of energy expenditure.

Shakra, ALE and Actitracker applications are easy to use because of the reason that user just needs to run the application and that rest of the operations are handled by the software. However, for Houston and Chick Clique, user needs to manually enter his total number of steps everyday.

<b>Application</b>	<b>Easy to Use</b>	<b>Objective</b>	<b>Accuracy</b>	<b>Motivation</b>	<b>Intensity</b>
Shakra	+	o	o	+	-
Houston	-	+	o	+	-
Chick Clique	-	+	o	+	-
ALE	+	+	o	+	+
Actitracker	+	+	+	+	+

Table 3: Comparison of Research Deployments; ( “-” : not achieved, “o” : partly achieved, “+” : well done.)

We have presented some research deployments for health promoting tools and reviewed the methods and technology used in them. In connection with our scenario presented in Section 2, Actitracker and ALE come closest to provide an accurate result when it comes to detecting activities by smart phone sensors. Our task is to verify the usefulness of the methods, extend them for classification of an “activity zone”, measuring both activities and the level of the activities. Our goal is to create a state of the art overview in mobile-supported activity monitoring, to perform a prototypical implementation, and to evaluate the limits of mobile-based monitoring. Our focus is on observing the correlation between HR measurements and accelerometer sensor results, not on finding or improving an algorithm for activity detection. In this regard, we prefer using the activity detection method of ALE

which seem to provide good accuracy results for the predefined activity types (slow walking, fast walking, slow running and fast running) in our scenario.

### **5.2.2 Products for Health Promotion:**

In the previous section, we gave an introduction to the research deployments for health promotion tools, now we are going to introduce the following products and trends that are currently used in today's modern market. Such products also help people to get aware of the intensity level of their activities, to reach an activity level to be healthier, and keep track of their daily routine in terms of activity levels. Examples of such products are SenseWear as a portable clinical device focusing on determining metabolic PA and estimating energy expenditure, Fitbit and similar kind of devices (e.g. Nike Fuelband, Jawbone, etc.) focusing on keeping the track of user's PA, S-Health concept introduced by Samsung focusing on involving different kinds of sensor technologies in order to help users to achieve their fitness goals, and computer games focusing on encouraging people to get physically active.

#### **5.2.2.1 SenseWear also known as BodyBugg**

It is a clinical product developed in order to address the need of a product providing easy, accurate and cheap way of determining metabolic PA and estimating energy expenditure. It is a portable device that is composed of many sensors as shown in Figure 22. The dedicated application installed on a computer could be synchronized with SenseWear and allow the user to view his total energy expenditure (MET), PA levels, calories burnt, steps and sleep efficiency [73]. The validation of the product is conducted against Doubly Labelled Water (DLW) methodology (see Criterion methods in section 5.1.2). There was an underestimation of 8.5% in the daily energy expenditure compared to the results with DLW methodology [11].

As it is stated before, it is a clinical product and I think that it is not a suitable device to use in a daily life because of its size and design in comparison with Fitbit device that we will mention in the next subsection. Briefly, because of its results being accurate, rather than as a tracking device, SenseWear is used as a standard to evaluate the accuracy of an application just like applied for the evaluation of the accuracy of ALE.



Figure 22: The SenseWear Pro armband (2000-2003)

### 5.2.2.2 Fitbit, NIKE Fuelband, Jawbone, Basis

Such devices are personal fitness tracking products that motivate users to be more physically active by allowing users to view their activity levels and amount of calories burnt. Fitbit, Nike Fuelband, and Jawbone are wrist-worn, while there are also products like Basis as a fitness watch. They collect data mainly from the built-in accelerometer sensors and provide information about the activity level of the user.

The advantage of such devices over using a smart phone as an activity tracker is their battery life. As an example, the device “Fitbit Force” can last about 7 days to 10 days [74] while the battery of today’s smart phones cannot last that long. We will point out this problem and make a connection with Fitbit like devices in Section 7.2.

### 5.2.2.3 Smart Phones for Health Promotion

Smart phone producers come up with new concepts in this area to dominate the market. S-Health is an example of such concepts. It is a new concept that came up with the release of the product GALAXY S4 by one of the leaders in mobile technology, Samsung. The main purpose is to help users achieve their fitness goals by keeping track of their fitness levels during workouts and throughout the day. A heart rate monitoring device called HRM could be integrated into S Health, which enables users to check their exercise intensity, or a body weight tracker measuring weight could send the weight history of the user to S Health app, or a wrist band called S Band like Nike Fuelband,

and Fitbit gets involved and measures the activities of the user under the concept of S Health [57].

### **5.2.3 Games for Health Promotion:**

Besides research deployments and commercial products, there have also been some computer games released that encourage PA. Sunny et al. [12] provides an analyses of these games. Nintendo’s “Pocket Pikachu” is an example of such games marketed to children, in that there is a character who reacts to step count of the user. The character gets happier as the step count increases. “Get up move” is another video game encouraging weight loss by giving commands to the user to move in a pattern on a special floor mat. Briefly these fitness games that provide the player with physical exercise motivate user to be more active by making exercise more fun.

## **5.3 Evaluation and Recommendation**

We have explained the measurement techniques classifying activity types and calculating the intensity of activities. We introduced research deployments and real life products for health promotion, and last trends in the area.

From the discussion we had about methods regarding the calculation of the intensity of activities, objective methods rather than other methods fit in our scenario because of the reason that we are out after mobile-supported activity monitoring. Yet, criterion methods are not feasible due to their expensiveness and laboratory setting, and subjective methods are not convenient for individual analysis of PA.

We aim to create a state of the art overview in mobile-supported activity monitoring and perform a prototypical implementation. Our prototypical implementation is to be built upon activity detection and activity zone detection.



## 6 Implementation and validation

In this section, we are going to present the implementation and validation of our study by giving an analysis of capabilities of our study. The implementation in our work is to define an application for the feedback of activity level.

We can split our implementation into three main parts;

1. Training mode
2. Application mode
3. Reporting mode

We will provide the implementation of these aspects and validation of the application. First in the following subsection, we will give our implementation plan representing the process starting from the retrieval of first acceleration signal of the mobile phone to defining activity zones for the user. After explaining that data flow from the beginning to the end, we will touch upon each implementation aspect of our study.

### 6.1 Implementation Aspects

The main contribution of this study is to understand how much we can get about the user's activity zone without using an external sensor. That's why we preferred focusing on observing the correlation between HR measurements and accelerometer sensor results rather than finding or improving some algorithms for activity context detection. For that purpose, instead of reinventing the wheel in order to be able to detect activities of the user, we take the implementation of "Activity Level Estimator (ALE) [11]" as our reference.

At this point, it is important to note that the only reason for us to benefit from the implementation of ALE is to collect accelerometer sensor data in an appropriate way meaning that without noise and any gravity. Jody [11] is out after detecting different types of activity, while we aim to define activity zones by correlating acceleration data and heart rate measurements. Briefly, we will follow the steps taken by Jody in order to end up with suitable acceleration data sets enabling us to correlate with HR measurements and by this way to create activity zones.

In our project, we have identified two relevant classes of information that we collect by pervasive devices; physiological and behavioural information. We benefited from the Zephyr HR sensor for physiological information and 3D accelerometer sensor of the smart phone for behavioural information in order to define activity zones of the user.

The process of achieving the activity level is as follows;

1. **Analysis of raw accelerometer data**
2. **Enhancement of data quality and analysis**
3. **Detection of activity zone of the user**
4. **Estimate Heart Rate ranges for each zone**

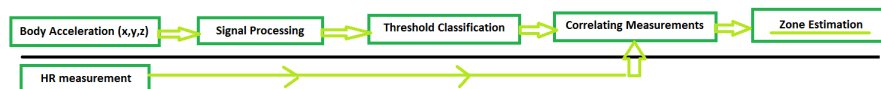


Figure 23: ZE Process

We first analysed the raw acceleration data retrieved from the smart phone’s accelerometer sensor in order to be able to detect the activity of the user (if walking or running). This step is applied in both training mode and application mode of our application for the purpose of ending up with specific ranges for each activity.

After a period of each time when adequate number of sensor data packages are collected for data analysis, as successfully applied for ALE, we also removed gravity from acceleration values and applied a couple of noise filtering algorithms in the signal in order to enhance the quality of data for activity zone detection. Finally, we were able to define our activity ranges for walking and running at different speeds (km/h), to which heart rate ranges are attached.

The following subsections will explain each of these steps in detail. It is also important to note that the steps in next subsections are related to only the built-in accelerometer sensor of smart phone and processing that acceleration data for context detection. Our external HR sensor, the Zephyr device, which is used for physiological information is not exposed to any

filtering algorithm or any other. It is because we assume that the Zephyr external HR device functions accurately and sends its data to the application in an accurate way. In this regard, the filtering operations that we mention in the following subsections only relate to the accelerometer sensor of the smart phone.

### 6.1.1 Sensor Logging and Analysis

In this subsection, we are going to explain how we retrieve accelerometer sensor data from our smart phone's built-in accelerometer sensor and log the incoming data, and also how we analyse it.

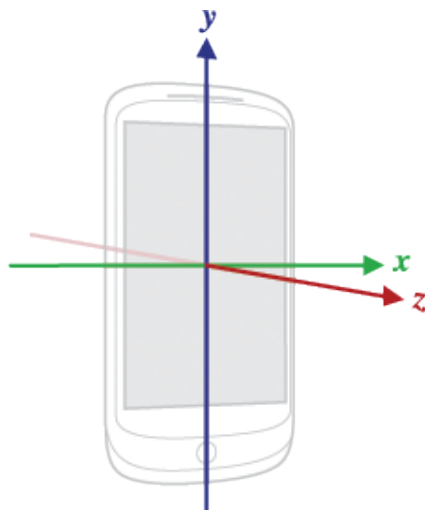


Figure 24: Coordinate system used by the Sensor API [75]

For activity detection and monitoring three-dimensional device movement, the accelerometer sensor of the smart phone is used in our study. As the official web-site of Android mobile development [75] provides that “the built-in accelerometer sensor measures the acceleration force in  $m/s^2$  that is applied to a device on all three physical axes (Figure 24), including the force of gravity”. As given in this definition, the force of gravity is included to the acceleration and affects the signal in a way that prevents us from having a right signal for activity detection [11]. This effect is represented in Figure 25, which suggests that the gravitation force of the ball representing a sensor would be:

$$\begin{aligned} X &= 0 \\ Y &= 0 \\ Z &= -9.81 \text{ m/s}^2 (-1g) \end{aligned}$$

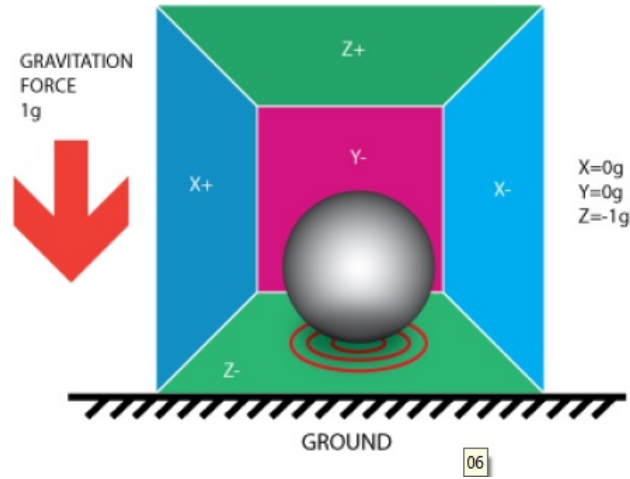


Figure 25: The ball represents the gravity force applied on the ground that is measured by accelerometer [11]

For the removal part of gravity effect from acceleration, we used the high filter pass algorithm that is described in Section 6.1.4.

Each time the accelerometer sensor sensed an acceleration, the built-in sensor sends new values  $(x, y, z)$  in  $m/s^2$  to the device, we filter these incoming values and then calculate the vector of acceleration and log the results into a file.

After applying the filtering algorithms for the removal of gravity effect and smoothing the signal, we calculate the vector of total acceleration. The purpose of computing the vector is to end up with a single value out of three values  $(x, y, z)$ . By this way, we are able to calculate the total acceleration.

For the vector of acceleration, we use the following equation which is called Dot Product [11] ;

$$Va(m/s^2) = \sqrt{x^2 + y^2 + z^2} \quad (1)$$

In order to clarify the benefit of using dot product and coming up with a single value, we will share two charts. The first chart in Figure 26 consists

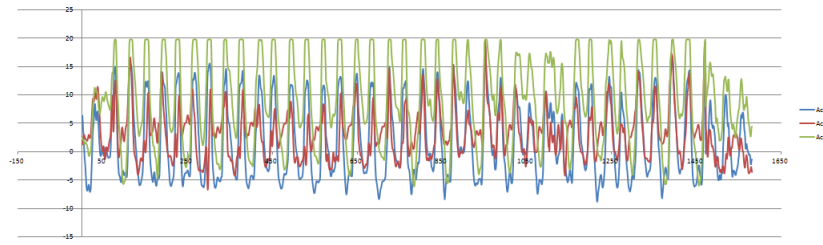


Figure 26: A sample of collected accelerometer sensor data in 3 axes for the activity of running

of 1580 data points collected after taking a running activity. After applying dot product algorithm in order to calculate vector of acceleration, we end up with the chart given in Figure 27.

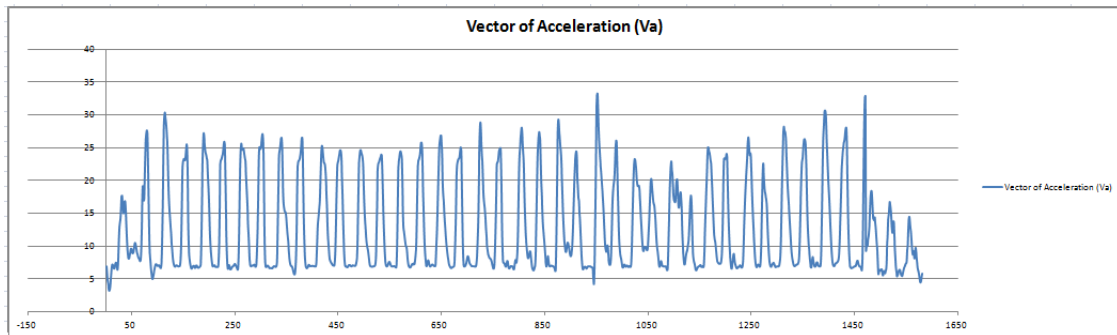


Figure 27: An example of vector acceleration

In this subsection, we explained the incoming accelerometer x, y and z values, the gravity effect and the calculation of acceleration vector. Another important aspect in fetching sensor data from the built-in sensor is to know at what pace we need to listen to the accelerometer sensor and calculate the total acceleration. We will now explain this in the following subsection.

### 6.1.2 Sampling Rate

Sampling rate or also called data delay is the rate at which sensor data is delivered to the application. However it is important to keep in mind that sensor data is not delivered to the application directly meaning that the

sensor framework contacts with sensor events first and then the application acquires these sensor events via `onSensorChanged()` callback method [75].

Android SDK enables developers to specify different data delays in order to control the interval at which the sensors are being listened to. These delay modes are classified based on their frequency of update in microseconds ; Normal, Game (20.000 microsecond delay), UI (60.000 microsecond delay) and Fastest (0 microsecond delay) modes. Besides that developer is also able to manually configure this interval based on his needs. Each time when the interval passes away, `onSensorChanged()` method is called and sensor events are sent to the application.

Selecting the sampling rate is a vital decision to make since it is highly related to one of the biggest concerns in the area, the power consumption of the mobile phone. If the delay is larger, a lower load is imposed on the processor which means that the battery consumes less power. Although it is better to choose larger delays for the sake of battery consumption, the decision should be made considering the type of the application that is to be developed. However regarding our study, we only focus on the feasibility aspect, thus looking for a method to work rather than optimizing the work for battery power. In summary, it is not our concern to keep battery consumption in minimum in our current study. Battery power considerations related to sampling rate are covered in Section 8, Discussion and Future Work.

Other than battery power considerations, for activity detection applications, choosing the right sampling rate is also important to define ranges for different activity types in order to have minimum amount of noise. We ran context detection mechanism with different sampling rates and our conclusions were similar to Judy's [11]. For Zone Estimator (ZE), we choose UI mode (60.000 ms delay) as the optimised rate. For activity types discussed before, we could choose higher sampling rates as well, however we experienced huge amount of noise with higher rates like DELAY GAME due to the reason that even slight movements were sensed with such a high delay rate. On the other hand, small delays would cause us to end up with bad precision since most of the acceleration is ignored.

In conclusion, we explained the importance of selecting the right delay mode for the systems using mobile sensors. DELAY UI, 60.000 microsecond delay is the best option for us to detect the activity types we mentioned earlier in an accurate way. Furthermore, choosing this delay mode is also advantageous in terms of battery consumption. However, we will take this topic as our future work. In our experiment, we observed that for each second

approximately 100 accelerometer sensor values are retrieved by the system. In the following section, we will explain how we interpret these data packages.

### 6.1.3 Data Interpretation

In this section, in order to explain how we interpret the signal, we provide an example that is well analysed by Jody, one of the creators of ALE. The signal retrieved from the accelerometer sensor includes so much peaks and noises which does not correspond to walk movements at all. Jody tried to find out which peak represented a step and which was just a noise [11]. He provided a decomposition of a walk movement created in Autodesk 3dsMax as given in Figure 28.

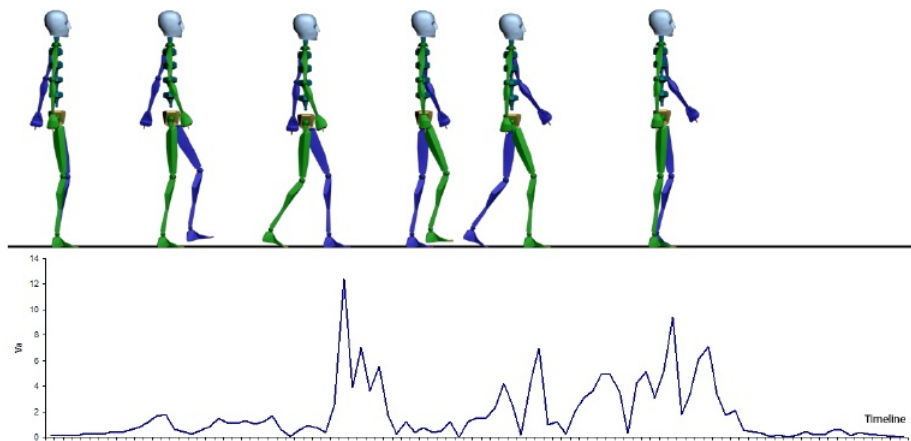


Figure 28: Decomposition of a walk movement when the phone is in user's pocket [11]

He analysed this decomposition in an empirical way and came to the following conclusions. First, he saw that even when the user stops stepping, noise may occur in the signal because the mobile phone may keep bouncing in the user's pocket. Second, he observed that the level of peaks may differ based on which leg moves forward and touches the ground. He states that if the movement is made on the same side of the mobile phone then the peak is stronger. These are reasons why the raw signal includes noises and irrelevant peaks as well as we experienced the same in our raw signal for walking (Figure 26). This kind of signal cannot lead us to accurate activity ranges. That's

why, we need to use some mechanisms to remove noise from the signal and to end up with separate ranges. The following subsection describes some filtering mechanisms that help us remove noise from the signal.

#### 6.1.4 Signal Filtering

We will now explain why and how signal filtering algorithms are used in our study. First, we explained in Section 6.1.1 that we retrieve three acceleration values including the force of gravity from the accelerometer sensor. We declared that we use high pass filter in order to remove gravity. In this regard, first step is to apply high pass filter on incoming data set (x, y, z). The following Equation (2) sends the data of acceleration in three physical axes (x, y and z), and gets them back after each value is filtered by high pass filter algorithm. The code of this filtering algorithm is provided in Appendix C.

$$highPassFilteredVals = highPass(accX, accY, accZ); \quad (2)$$

After getting rid of the force of gravity, next step is to calculate the vector of acceleration, which is already explained in Section 6.1.1. At this point, now we have a single value (Va) out of three values (x, y, z), which is assumed to have no gravity at all.

Other than the force of gravity, the incoming signal may include noises and irrelevant peaks because of the reasons given in the previous subsection. We also have a noisy signal as given in Figure 29 which causes us to end up with overlapping acceleration ranges for the activity types; walking and running.

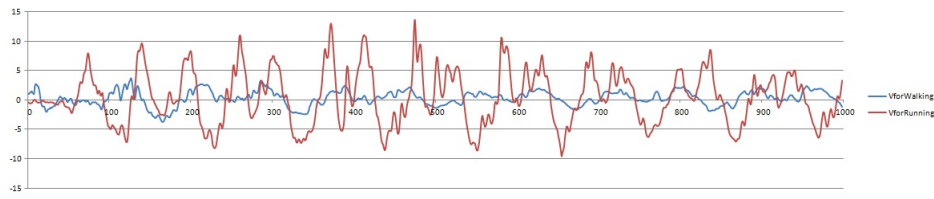


Figure 29: Raw signal Va for walking and running

It is important for us to come up with less overlapping data ranges due to the reason that in this way it would be more appropriate for us to differentiate each activity type from each other. In our study we are out after



detecting walking and running activity types. As stated before, our focus is on observing the correlation between HR measurements and accelerometer sensor results rather than studying how to detect activity context. For this reason, we applied the techniques used by Jody for the activity detection functionality of ALE (Figure 30). In this section, we provide two filtering mechanisms that remove the noise from the signal; maximum filter and average filter.

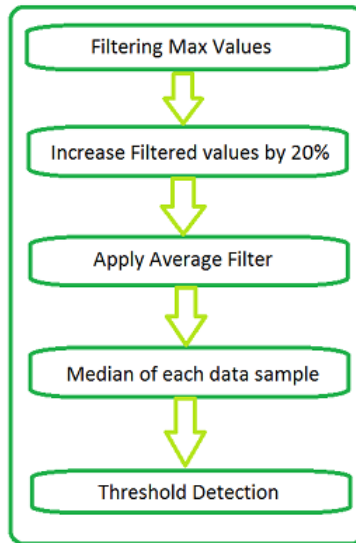


Figure 30: Life cycle of the data filtering functionality [11]

Maximum filter is used in order to eliminate low values and to keep only high values on a time window. Jody used the term “data point” for each vector of acceleration that we mentioned earlier. He suggested according to his experiments that applying maximum filter on a sample at exactly 16 data points is the optimum option rather than taking a smaller or bigger size of the sample. He observed that a smaller sample keeps noisy information, while a bigger one removes the peaks from real acceleration [11]. We also take 16 data points to compose a sample, and used the same logic for applying the maximum filter over our signal. After applying the maximum filter on all of the samples, we end up with a list of maximum numbers.

In order to make it clear, we provide an example explaining each of these

steps; Figure 31 demonstrates sixteen data points of a sample which is retrieved from a result of a real experiment. Each sensed data (x,y,z) is first exposed to high pass filter to eliminate gravity effect, and then put into the table as shown.

<b>Data Point</b>	<b>Acc X</b>	<b>Acc Y</b>	<b>Acc Z</b>	<b>Vector (Va)</b>
<b>1</b>	<b>-0.009</b>	<b>7.123</b>	<b>1.539</b>	<b>6.538</b>
<b>2</b>	<b>1.893</b>	<b>9.166</b>	<b>0.885</b>	<b>7.205</b>
<b>3</b>	<b>1.303</b>	<b>8.281</b>	<b>0.776</b>	<b>7.355</b>
<b>4</b>	<b>0.617</b>	<b>7.246</b>	<b>0.313</b>	<b>7.478</b>
<b>5</b>	<b>-0.022</b>	<b>6.388</b>	<b>-0.558</b>	<b>7.382</b>
<b>6</b>	<b>-0.425</b>	<b>6.184</b>	<b>-1.471</b>	<b>6.892</b>
<b>7</b>	<b>-0.345</b>	<b>6.184</b>	<b>-1.812</b>	<b>6.919</b>
<b>8</b>	<b>0.374</b>	<b>7.709</b>	<b>-0.667</b>	<b>6.606</b>
<b>9</b>	<b>1.447</b>	<b>9.67</b>	<b>0.327</b>	<b>5.734</b>
<b>10</b>	<b>1.676</b>	<b>10.351</b>	<b>1.144</b>	<b>4.822</b>
<b>11</b>	<b>1.694</b>	<b>10.365</b>	<b>1.798</b>	<b>4.631</b>
<b>12</b>	<b>1.402</b>	<b>9.602</b>	<b>2.315</b>	<b>5.285</b>
<b>13</b>	<b>0.257</b>	<b>8.063</b>	<b>2.043</b>	<b>5.652</b>
<b>14</b>	<b>-0.885</b>	<b>6.851</b>	<b>1.022</b>	<b>5.612</b>
<b>15</b>	<b>-1.645</b>	<b>6.211</b>	<b>0.041</b>	<b>5.285</b>
<b>16</b>	<b>-2.038</b>	<b>5.843</b>	<b>-0.545</b>	<b>5.08</b>

Figure 31: An example of a data set consisting of 16 data points

As illustrated, the first column represents the number of data point, the next three columns are for three physical axes (x,y and z), and the last column represents the vector of three physical axes. Given that we have a set of 1600 data points created after collecting sensor data for 5 minutes. Figure 31 illustrates the first sample of 1600 data points. After calculating the vector of acceleration for each data point, next step is to apply maximum filter over the calculated vector values of each data sample (16 data points).

As mentioned before, the maximum filter is to keep only high values and discard low values. Maximum filter extracts the maximum number from each data sample. The algorithm of maximum filter [11] is given in Equation 3 and 4 as follows;

Round 1:

$$\begin{aligned}
 a &= \text{elementOfTheSignal}(Va) \\
 \text{sample}(\text{size}16) &= [a; a + 1; \dots; a + 15] \\
 a\text{Filtered} &= \text{MAX}(\text{sample})
 \end{aligned}
 \tag{3}$$

Round 2:

$$\begin{aligned}
 a + 1 &= \text{elementOfTheSignal}(Va) \\
 \text{sample}(\text{size}16) &= [a + 1; a + 2; \dots; a + 16] \\
 a - 1\text{Filtered} &= \text{MAX}(\text{sample})
 \end{aligned}
 \tag{4}$$

Second step as suggested by Jody is to increase these calculated maximum number by 20%, which affects the next calculations in a positive way for the purpose of increasing the interval between thresholds.

We provide an example of a data set which is exposed to maximum filter as given in Figure 32. As can be observed, low values are removed from the signal and the result of each maximum filter operation is increased by 20%.

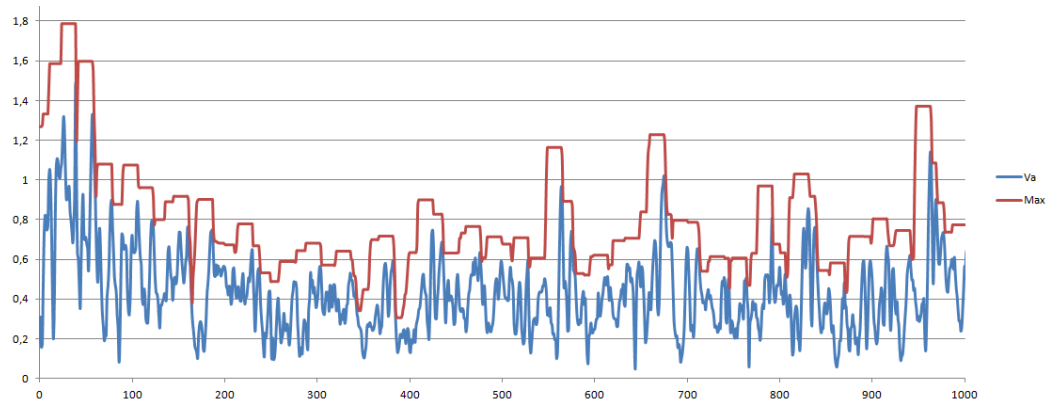


Figure 32: An example of a data set consisting of 16 data points

Average filter is applied over the data set which is just filtered by the maximum filter. The average filter is used in order to have a smoother signal, Jody suggests. After ending up with a list of maximum values that are increased by 20%, we can apply the average filter in order to remove the rest of the noise and make the signal smoother. For average filter, it is suggested to take not 16 data points this time, but to take 8 data points to compose a data sample as given in Equation 5 and 6. More information

about the insights of these filtering mechanisms, and the reasons for selecting these specific number of data points to compose a data sample could be found in [11].

Round 1:

$$\begin{aligned}
 a &= \text{elementOfTheSignal}(Va) \\
 \text{sample}(\text{size}8) &= [a; a + 1; \dots; a + 7] \\
 a\text{Filtered} &= \text{AVG}(\text{sample})
 \end{aligned}
 \tag{5}$$

Round 2:

$$\begin{aligned}
 a + 1 &= \text{elementOfTheSignal}(Va) \\
 \text{sample}(\text{size}8) &= [a + 1; a + 2; \dots; a + 8] \\
 a - 1\text{Filtered} &= \text{AVG}(\text{sample})
 \end{aligned}
 \tag{6}$$

As shown in Figure 33, we have removed the rest of the noise and ended up with a smoother signal after applying the average filter.

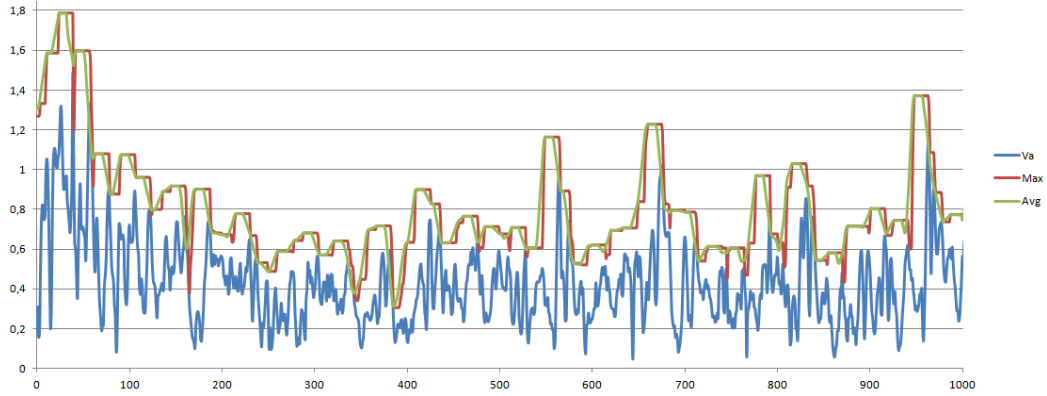


Figure 33: An example of a data set consisting of 16 data points

In this subsection, we explained what filtering mechanisms we benefited from to remove noise from the signal. After using these filtering mechanisms, we retrieve a list of average values at the end of the day. We will now explain how we make use of these values for the benefit of threshold determination.

### 6.1.5 Threshold determination

We have stated it is important for us to define non overlapping ranges, because non-overlapping ranges make the determination of HR easier. We will

analyse all of the four cases of slow walking, fast walking, slow running, and fast running in order to see whether we can present independent cases, thus making it easier to apply HR zones to them. However, we experienced some overlapping of acceleration ranges under some circumstances. We will point out these conditions later in this subsection.

We will now explain the next step which is to define ranges for each activity. First of all, it is important to remember that we have four types of activities; slow walking, fast walking, slow running and fast running.

In the previous subsection, we described the filtering mechanisms to remove noise from the signal. We first applied the maximum filter in order to eliminate low values, and then applied the average filter to make the signal smoother. After calculating the average values, we have one more step for the creation of threshold table. Before explaining what the next step is, we can provide a recap of what operations taken so far; we applied maximum filter, increased the found results by 20% and then applied the average filter over the results.

The last step is to define activity ranges. Jody presents a new method for this purpose, which is to find the median of each data set rather than taking the average of results which is a common method in other researches. It means that we will split the total result list into a number of groups according to a predetermined time window (e.g 2 seconds of data samples), and then find the median of each data set.

<b>Activity Type</b>	<b>Acc Min</b>	<b>Acc Max</b>	<b>Mean</b>
Slow Walking	2.13	3.1	2.6
Fast Walking	4.46	6.33	5.4
Slow Running	8.27	11.64	10.5
Fast Running	12.27	14.05	13.82

Table 4: Threshold Table Created after the Training Phase using LG G2

He states that median works better since the average is too influenced by peaks from the noisy information. It is also well applied to our results and

we are able to define non overlapping ranges for each activity (Table 4). In the following section, we will explain how we benefit from the threshold table for the learning module, and show how we define the activity zones.

## 6.2 Learning Module

The process of defining the activity ranges is handled for the learning phase. In relation to the activity types, we created activity zones representing the intensity of activities; red, orange, yellow, light green, and green zone. Each zone consists of an activity type, acceleration and HR values. We handle the HR measurement by an external HR device during the learning phase and HR values are recorded simultaneously with the acceleration that is being calculated as explained in the previous subsections.

Zone	Activity Type	Acc Range	Mean	HR Range	HR Mean
Orange	Slow Walking	2.13 - 3.1	2.6	89 - 108	96
Yellow	Fast Walking	4.46 - 6.33	5.4	104 - 116	112
Light Green	Slow Running	8.27 - 11.64	10.5	121 - 137	127
Green	Fast Running	12.27 - 14.05	13.82	137 - 151	145

Table 5: Table of Activity Zones

The user repeats the same operation for each activity type for five minutes; slow walking, fast walking, slow running, and fast running. When the learning phase is over, activity zones are defined successfully as shown in Table 5. Then, the application mode could be started and the rest part of the functions are handled by the ZE application. Now, we will define our reasoning module used in the application mode.

## 6.3 Reasoning Module

When the user starts the application, ZE starts to estimate the activity zone of the person by comparing the current acceleration values of the smart phone with the ranges created during the learning phase as explained in the previous subsection. ZE collects acceleration values of the last 20 seconds of the period of time, applies the methods described in Section 6.1, and then ends up with a median accelerometer value which is compared against the data ranges formed in the learning module. According to the range into which the current acceleration falls, the ZE estimates the activity zone of the

person. During the day, the system shows a colourful sign which indicates the current activity zone of the person as demonstrated in Section 3.1.1. For instance, a green symbol is shown to indicate that the user has achieved a 30 minutes of activity.

## 6.4 Implementation Remarks

This subsection provides some implementation remarks on our study. We have conducted an experiment in order to see the correlation between acceleration and HR values of the person. For this purpose, we let the user start training at different speeds. The user held the smart phone in his palm, wore the HR sensor and started to perform walking activity at 3 , 4 and 5 km/h, and then started to perform running activity at 6, 7, 8, 9 and 10 km/h respectively. We share the results of this experiment in Table 6. As could be observed, both the acceleration and HR values increase with the increase of speed (km/h).

Activity No	Activity	Speed (km/h)	Median Acc	Median HR
1	Walking	3 km/h	3.1	91
2	Walking	4 km/h	4.2	99
3	Walking	5 km/h	5.0	110
4	Running	6 km/h	13.5	134
5	Running	7 km/h	15.5	133
6	Running	8 km/h	14.9	143
7	Running	9 km/h	15.5	150
8	Running	10 km/h	20	158

Table 6: The results of an experiment in which user started to walk at 3 km/h, increased his speed by 1 km/h after each 5 minutes of activity, and ended the experiment after running at 10 km/h.

We created two linear regression figures with the results shared in Table 6. Our purpose was to see the linear regression of two parameters; acceleration and HR as given in Figure 34 and 35. The equation ( $R^2 = 0,96$ ) of the linear regression for walking activities shows in Figure 34 that there is a strong correlation between two values. 0.1 means that on average, acceleration is going up about 1 for each 10 heart beats. On the other hand, when observing the linear regression line for running activities, the equation is  $R^2 = 0,66$

meaning that the correlation is weaker in comparison with the results of walking activities. The decrease in the correlation is because running at 6 km/h and 7 km/h resulted in almost the same HR values and running at 7 km/h caused to bigger acceleration in comparison with running at 6 km/h. For running activities, acceleration is going up around 1,8 for each 10 heart beats, which shows that high intensity activities end up with bigger acceleration per heart beat in comparison with low intensity activities.

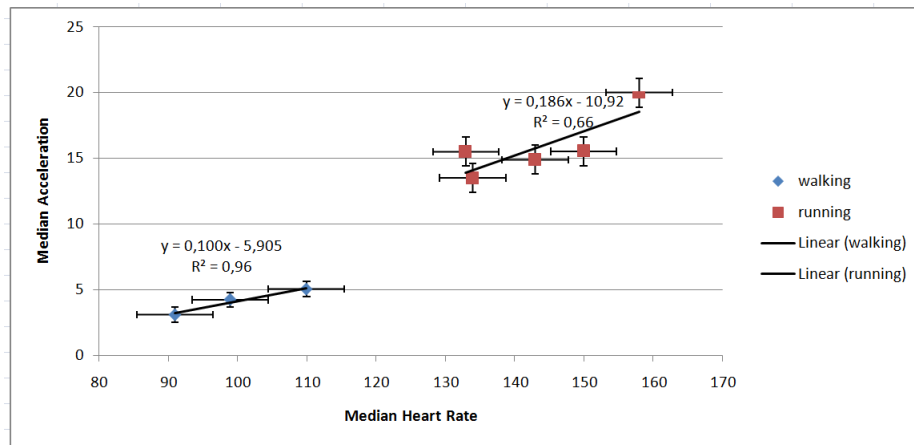


Figure 34: Linear Regression of Acceleration and HR values , HR in X-Axis

In Figure 35, we recreated the graph by switching the axis of parameters. For walking activities, on average, there is an increase of 9 to 10 heart beats for each acceleration value, while HR increase is 3 to 4 for the running activities. We could conclude based on this fact that high intensity activities result in smaller HR changes per acceleration.



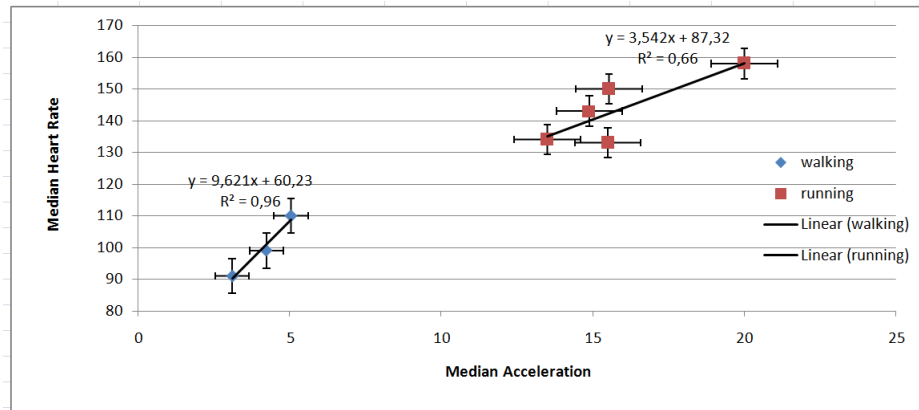


Figure 35: Linear Regression of Acceleration and HR values, Acc in X-Axis

In this chapter, we have described implementation aspects of our study in detail and presented implementation remarks. Now, we are going to evaluate our work by covering the parameters which affect the accuracy of our results.

## 7 Evaluation

In this section, we are going to evaluate our study including the application ZE, that provides a feedback of activity level. We aim to explain the parameters affecting HR and acceleration values, and also the correlation between them. We will evaluate our study in connection with the life cycle of the data filtering functionality of our study, which was previously demonstrated in Figure 30 in Section 6.1.4.

To evaluate the performance of ZE, we performed several series of experiments to validate activity zones created during the training phase where the correlation is actually formed. During the time of our study, we conducted different kinds of experiments that we can split into two groups; minor and major experiments. Minor ones are aimed to serve for a specific purpose such as to help us improve our system for the sake of accurate and reliable results (e.g. taking a running activity for two minutes to check if the sampling rate for accelerometer sensor is set correctly for the determination of the activity), while major ones encompassing each functionality of our study are to provide an analysis of our activity zone estimation system (e.g. running the application with all functionalities, and completing the training phase with performing each activity as asked). For both kinds of experiments, we followed the aforementioned procedure explained in Section 2.1 to perform an activity, or series of activities. Therefore, it should be noted that our evaluation criteria are formed considering that aforementioned procedure of performing activities.

As a matter of fact, there are several factors to evaluate within the scope of our study, however an evaluation covering the all affecting parameters entails a control group by which we could analyse experiments on a large sample. Our goal was to create a state of the art overview in mobile-supported activity monitoring and perform a prototypical implementation. Because of the reason that we look after a prototypical implementation, we only focus on the parameters that are the most important ones to look at, thus other parameters still remain as our future work.

We formed our evaluation criteria by taking a subset of all factors that may affect any process given in Figure 30 into consideration. We have organized our evaluation criteria under three main categories; sensitivity, mobile phone capabilities, and security.

We will provide a sensitivity analysis of ZE in order to explain how cer-

tain it is under different circumstances (e.g. performing the activity with a smart phone worn by an armband), and we will explain the factors that may influence the result of our study (e.g. elevation of the ground, brand of the smart phone), plus we will provide an evaluation of our study considering the capabilities of the smart phone such as battery and CPU power. Last but not least, we will also touch a bit on the security aspect of our study. Then, we will summarize the difficulties and issues that we faced during our study and we will criticize and put comments on our methods.

## **7.1 Sensitivity**

Now we are going to provide a sensitivity analysis of our study. We will first discuss how the position of the smart phone affects the acceleration results, then provide our results retrieved by using two different smart phone brands, explain the difference between performing the activities on a treadmill and racecourse as well as explain how slope of the ground on what the user performs his activities affect the detection of his activity.

### **7.1.1 Different position of the Smart Phone**

In this subsection, we will explain how the acceleration results are affected by the position of the mobile phone. In order to make an observation, we have conducted four experiments to analyse the sensitivity of our activity detection system. The two of the experiments were conducted when the position of the phone is “with-armband” and the two for the position “in-palm”. We provide the results of the experiments in Table 7.

Considering the results found for the position “arm-band”, the first observation made is that because of the angle of the mobile phone is different, we end up with a different amount of acceleration than we have had for the position “in-palm”.

Experiment No	Position	Slow Walking	Fast Walking	Slow Running	Fast Running
1	Arm-Band	0.8 - 2.4	3.5 - 4.5	9.0 - 10.5	12.1 - 13.8
2	Arm-Band	1.1 - 2.1	3.2 - 3.6	8.7 - 9.2	11.0 - 12.3
3	Palm	1.4 - 1.5	2.9 - 3.1	8.6 - 10.5	11.1 - 13.6
4	Palm	1.3 - 1.5	3.0 - 3.4	7.9 - 8.7	11.6 - 13.0

Table 7: Comparison of Accelerometer Measurements According to the Position of the Smart Phone

Another important point to make is that results found for the position “in-palm” are more stable than the results found for the position “with- armband”, meaning that the results found for the position palm are close to each other for the experiment number 3 and 4, while we almost ended up two different ranges for slow running and fast running in experiments 1 and 2. We can conclude from this that our application is more accurate when the position is “in-palm” in terms of activity detection. Though not having the proof, we assume that running and walking are less disturbed by arm movements, thus the “in-palm” monitoring is more directly related to speed and the type of the movement.

### 7.1.2 Another Brand of Smart Phone

We are going to provide a comparison of two smart phone brands in terms of detecting the user’s activity by his acceleration. We have conducted our experiments on Samsung S2 and LG G2 when the position of the mobile phone is in palm.

Experiment No	Brand	Slow Walking	Fast Walking	Slow Running	Fast Running
1	Samsung S2	1.3 - 2.2	2.2 - 2.7	5.9 - 7.6	7.8 - 9.5
2	LG G2	2.5 - 2.7	5.2 - 5.6	9.7 - 11.6	13.2 - 14.1

Table 8: Comparison of Accelerometer Measurements based on the Brand of the Smart Phone

The results collected from the two brands are given in Table 8 which indicates minimum and maximum acceleration ranges for each activity types. For these two smart phone brands, the results vary up to as much as 100%, meaning that LG G2 reports double the accelerometer values as compared

with Samsung S2. When it comes to comparing the two brands, we observed that in comparison with the Experiment 2 conducted with LG G2, the variation of acceleration and the difference between minimum and maximum acceleration for each activity are considerably bigger for the Experiment 1 conducted with Samsung S2. We assume that it is related to the size of LG2 which is bigger than Samsung S2. S2 is a little bit easier to shake when performing the activity because it is lighter and smaller to grab compared to LG2. Such characteristics of S2 may result in a bigger variation in terms of acceleration. As an outcome of this experiment, we see the need for calibration for each new phone because of the reason that they may produce different acceleration which affect our learning and accelerometer data. We assume that the accelerometer recording comes from different chip sets used, thus an analysis of the chip sets used in the various phone levels might provide sufficient analysis about which devices to use. However, as measurements are quite related to the individual, we anyway need to do a personal training, thus the personal training should be conducted together with the personal phone.

### 7.1.3 Elevation

Another important aspect affecting the results is the slop of the ground on what the user performs his activities. In order to understand how the acceleration and HR measurements differ on a flat and inclined ground, we conducted series of experiments in a row. In the first experiment, the user performed the learning phase and let the system create activity zones on a tread mill with no incline for 5 minutes, and in the second, the incline of the ground was increased by 3% and 4%. Our purpose was to see the accuracy of our system with different slops.

Experiment No	Ground	Slow Walking	Fast Walking	Slow Running	Fast Running
1	Flat	2.5 - 2.7	5.2 - 5.6	9.7 - 11.6	13.2 - 14.1

Table 9: Acceleration results on a flat ground and inclined ground

In table 9, we share the accelerometer ranges of each activity, which was created during the learning phase that is conducted on a tread mill with no incline. The results collected from the experiments for the ground inclined by 3% and 4% indicate that there is a slight difference between the ground

types in terms of acceleration, meaning that for 3% and 4% inclined grounds, about 80% of the acceleration values fall into the ranges of flat ground.

The slope of the ground on that we take activities plays an important role in results not only for the accuracy of activity detection but also for the variance in HR values, which affects the accuracy of activity zone detection because of the reason that increasing the slope of the ground causes to increase in HR values. In order to evaluate this parameter, we conducted our experiments on different grounds such as roads with different elevations (e.g. racecourse), and on a treadmill.

Experiment No	Ground	Slow Walking	Fast Walking	Slow Running	Fast Running
1	Flat	99 - 110	102 - 114	115 - 125	135 - 143
2	3% Incline	100 - 105	110 - 116	119 - 128	140 - 145

Table 10: HR measurement results on a flat ground and inclined ground

Regarding the HR values, as previously stated, we expected to get higher heart rate values where the incline of the tread mill is increased, meaning that the challenge is bigger in comparison with the flat ground, thus the intensity of the activity is bigger. Table 10 proves that, when the incline is increased by 3%, the HR values are also increased by approximately 2 to 5 beats per minute for each activity type except slow walking. In this regard, for HR values, the elevation less than 3% is within the accuracy of 95% in our study. The incline greater than 3% needs to be evaluated. And our experiments show that the accuracy of activity zone detection is >80% upto 3% incline.

#### 7.1.4 Other Factors

There are some parameters that we have not evaluated yet, but they may have an effect on the correlation between HR and acceleration. The parameters that will be checked in our future might include the following parameters; gender, weight, height, cloth and shoe type.

In the research of ALE [11], they conducted several experiments to see if such parameters have influence on the acceleration vector. It was possible for them to evaluate only the following variables; weight, height and gender. Other parameters remain unchecked because of the reason that evaluating them requires different types of experiments. They have observed that height has more influence than weight and females have lower acceleration than

males. ALE was out after creating generic thresholds of acceleration values for predefined activity types, however in our scenario, we require training phase in order to create individual specific activity zones, meaning that no matter what the activity is, by including HR zones into the concept of activity zones, we are out after detecting the intensity of the activity. Linking to the results found in the study of ALE, we can evaluate such parameters in our scenario for an individual basis analyses. The reason for this is that the correlation created during the training phase could vary in comparison with the results collected during the application mode in user’s daily life. In other words, it is important to perform an evaluation of aforementioned parameters during the training phase and his daily life respectively. In this regard, we may need to check how such parameters (e.g. cloth and shoe type) have influence on the correlation between HR and acceleration values. In conclusion, we defer evaluation of such parameters to future work.

<b>Effect</b>	<b>Accuracy</b>
Location of the Phone	In Palm : >90% Armband : >75% for fast walking and slow running.
Phone Type	100% depends on the brand of the phone
Road Inclination	>80% upto 3% Incline
Gender	<10% [Ref] to be confirmed
Height	<10% [Ref] to be confirmed

Table 11: Table of Effects with Accuracy values

Our prototypical trials of phone variability, position of the smart phone, and elevation indicate that further studies have to be undertaken to specify the impact of these aspects of the zone estimation. However, based on our

results we believe that a training phase is sufficient to capture an adequate detection within 5-10% accuracy. Results are given in Table 11 to be more specific about how the accuracy of zone estimation is affected by each parameter. When using the smart phone with an arm band, the accuracy of ZE falls from 90% to 75% while trying to detect the activity zone of the user, which is the case for fast walking and slow running activity types. However, the acceleration of the smart phone with the armband position is bigger in comparison with the palm position for slow walking and fast walking. Thus, results are so increased with the smart phone on arm that they cannot be detected at all with the ranges created in the learning phase.

Regarding the brand of the smart phone, experiments showed that the correlation created in a smart phone are not valid to be used in another smart phone, meaning a new learning phase is required.

As discussed, road inclination has also effect on the accuracy of activity zone estimation because the posture of the person and the way he holds the smart phone cause a different amount of acceleration. Moreover, increasing the incline causes the intensity of the activity to increase as well, which means higher HR values. Our experience showed that ZE has an accuracy of about 80% upto 3% incline. Further studies need to be conducted to evaluate the grounds with more than 3% incline.

Besides the parameters that we evaluated (location of the phone, phone type, road inclination), we also provided the estimated effects of some parameters on the accuracy of our system within the light of literature review that we have made.

Other parameters that we will evaluate are the training condition of the user and age. We guess that the activity of slow walking could be a moderate activity for elderly and for the ones who have not done any exercise for a long time, while it is very low activity for young adults and for the ones who are in a good physical condition. We also defer it to future work.

### **7.1.5 Effect of Learning**

It is important to note that we did not use a calibration method for our HR sensor in learning phase, as we rely on Zephyr. Other than trusting the accuracy of HR values coming from the external sensor, it is also vital to be aware of on what conditions the HR values of the person vary. Heart rate depends on the actual condition of the user, which is about the level of hunger, how energetic the user is, and time of the day. We have experienced such



variance in our experiments as well. For instance, we performed two experiments with the same scope in different days and we ended up with different HR ranges for the same type of activity, which we believe is highly related to the current physical condition of the user. American Heart Association states that there are some factors that may affect heart rate, which are; air temperature, body position, body size, medication use [76]. Though we are aware of such effects, we defer evaluation of such factors to future work.

## **7.2 Mobile Phone Capabilities**

In this chapter, we evaluate the effects of ZE in terms of battery consumption and CPU usage of the mobile smart phone.

In Section 5.1.3.3, we touched a bit on battery capabilities of smart phones with multiple built-in sensors. We are aware of the fact that battery limitation of smart phones is a really important issue as increases of other applications like the move application has shown. Plus, energy is drained mostly by CPU processing and communication purposes (sending and receiving sensor data). In this regard, power consumption is related to the following actions;

1. **Active Sensor Measurement**
2. **Communication to External Sensors (via Bluetooth)**
3. **Calculations for the Detection of activity**
4. **Logging of Results**
5. **Screen Activity**

The next subsections will discuss the estimated amount of CPU usage and battery power of the smart phone. We discuss what functionality of ZE drains the power and exhausts the CPU of the smart phone. Moreover, we share our future plans in order to use mobile phone capabilities in an optimised way.

### **7.2.1 Battery Consumption**

When it comes to observing battery consumption, it is difficult to calculate energy consumption precisely caused by a specific application. Because there are many operations being handled by the operating system on the

background, and it is not easy to make an observation about how much battery power is drained by only our application. For such precise and accurate calculation, a special device measuring the amperes used by the phone in a given moment might be needed as used in the study conducted by Roy et al. [77]. Even though it is a vital issue to overcome considering the design of an activity monitoring system in a smart phone [78], it is important to note that optimizing power consumption is not our focus in this study. We defer this issue to future work. However, to have an approximate idea of how much energy is drained by ZE, we have benefited from the power resource information panel of the smart phone. Figure 36 shows a snapshot of measures of battery power when running our ZE application. Further experiments have been conducted to see which part of the application drain the most of the power. And we have experienced that ZE application consumes about 35% of the whole power. Now we discuss how total energy consumed by ZE is portioned among each functionality of it.

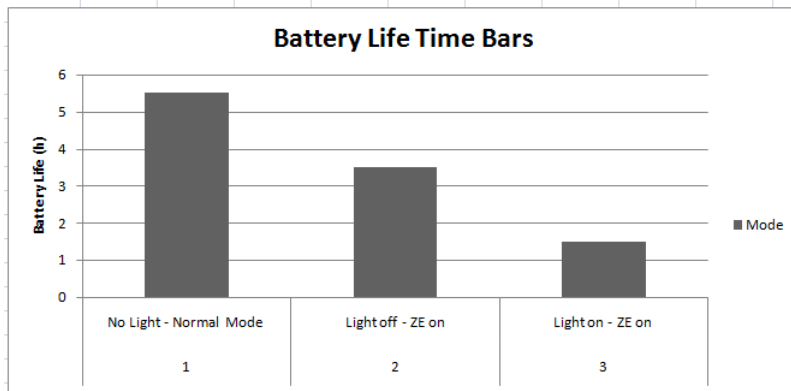


Figure 36: Battery Life Time of the Smart Phone (LG 2) with Different Modes

As previously mentioned in 6.1.2, choosing the right sampling rate is a vital decision to make not only for the application to run accurately but also for the sake of power consumption. We retrieve approximately 100 accelerometer sensor values per second, which may cause the CPU usage as well as the battery consumption to increase. We defer the evaluation of battery consumption in terms of sampling rate to future work.

Regarding the communication between the smart phone and the external

HR sensor, we stated in Section 4.5 that the Bluetooth communication technology is used in our study. The external HR sensor sends a BPM value per second to the smart phone. We have not evaluate the Bluetooth communication in terms of battery consumption. However, we expect that Bluetooth LE will be used for this type of communication between sensors. Moreover, we only make use of an external sensor during the training phase not during the application mode.

During the course of estimation of the activity zone, we log some results in the mobile phone's memory. However, such writing and reading operations are not a power killer like other parameters (e.g. screen light, high level CPU) that we will discuss next.

Another important factor reducing the battery power is related to how long and how often the display screen mode is kept on. We adjusted our application in a way that it displays the screen when only needed. Because of the results we found out in our experiment, we have experienced that screen light is one of the major drivers for power consumption. As demonstrated in Figure 36, the battery life of the smart phone is 3.5 hours when the screen light is off, while it is 1.5 hours when the screen light is on. It shows that, keeping the screen light on when ZE runs, power consumption goes up to 75% while it is 36% for ZE and screen light off. Briefly, keeping light on consumes more power than ZE algorithm.

As previously stated in Section 6.1.5, we calculate the mean acceleration of 2 seconds of data samples in order to do the zone estimation of the user. For the sake of energy consumption, we could improve our mechanism of activity cycle or use another program, thus reducing the power drained during the calculation. Another option of reducing the power might be to use additional sensors like the GPS or other sensors to get a better evaluation of the activity and only to use the accelerometer for the activity level. However, this is deferred to further work.

Considering our future work, when we need to put extra sensors into our scenario in order to detect other activity types, and when accuracy becomes an important matter to overcome, energy consumption in regard to accuracy will play an important role for the feasibility of our work. In this context, we may need to take a special care of the concept of battery consumption. For instance, when we involve GPS sensor into our scenario, being aware of the fact that the user is stationary means we do not need to know the speed or location of the user, thus we can stop employing the GPS sensor. Another mechanism could be an adapted sampling rate adapting itself based

on the activity context of the user. Such mechanisms optimizing energy consumption are also deferred to future work. Besides these, one might have to think about different design patterns for the phone itself if the phone is desired to use a platform. For smart phones, a similar design to Fitbit’s might be taken into consideration based on the fact that the device “Fitbit Force” using an accelerometer for the registration of activities can last about 7 - 10 days as previously mentioned in Section 5.2.2.2. There are estimation tools available as well which help developers to observe effects of design changes on power consumption [79]. We might benefit from such tools by integrating them into our study for the optimization of battery consumption.

### 7.2.2 CPU Usage

We have also observed CPU usage in Samsung S2 in order to see how much CPU usage is portioned for ZE. 6% of the CPU was busy for the idle mode without ZE, and as shown in Figure 37, we observed that ZE makes the CPU usage go up to 16% in average. From time to time, CPU value increases even up to 100%, it may be caused by the logging operation processing by ZE, or might be caused by other factors. The reasons for such increases might be studied in our future work.

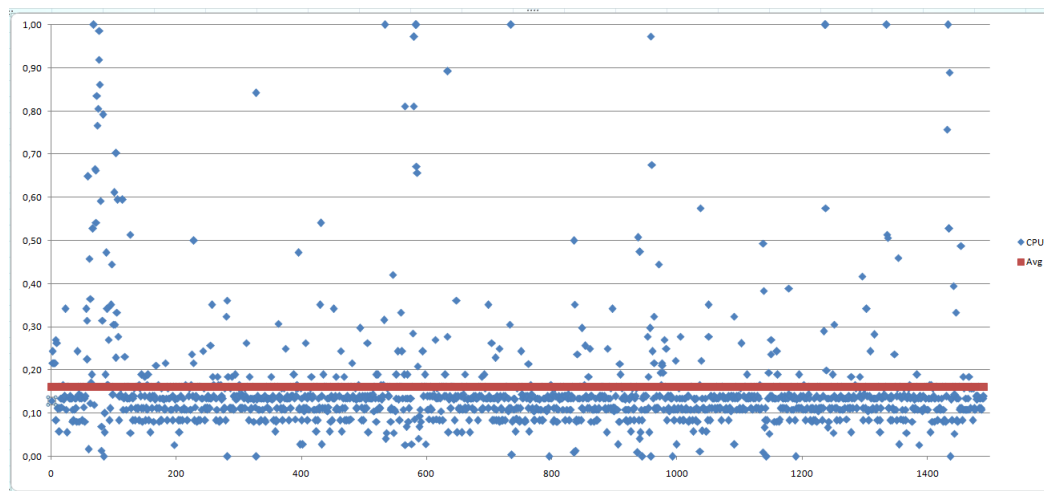


Figure 37: Statistic of CPU Usage in Smart Phone (S2) When both Screen Light is on and ZE are on

### 7.3 Security Evaluation

Even though we are aware of privacy and security of data related to health, our assumption is that the evaluation of these security and privacy aspects are outside of the scope of this study focusing on mobile phone capabilities. Privacy and security aspects are more related to the handling of the user data, both on the phone and in the cloud. Such analysis is left to related studies.

### 7.4 Lessons Learned

In the Evaluation Section, we have presented several aspects being relevant for development of our application. First, we provided a sensitivity analysis of our study, then touched on the mobile phone capabilities. Now we will give our remarks on the evaluation part.

Our study had the focus on the capabilities of the mobile phone. Thus, absolute values for activity measures and calibration of activity zone for larger user groups has not been the focus. Our ZE method was conducted by a small number of groups. And our best guess is that we need a much larger group at least 10 to 20 people to repeat the experiments in order to see how applicable the method is for common use. By this way, we could be able to see if our correlation method works for a group of people with different characteristics (length, weight, etc.) with different smart phone brands.

Regarding the sensitivity analysis, there are few points to make in order to ensure the feasibility of our application. Devices such as Fitbit have the advantage of being worn on the same position (wrist) all the time, which results in no variation, while smart phones can be carried in different parts of the body (e.g. pocket, palm, armband). Instead of forcing the user to carry the phone in the same way he did for the training phase, a system that can detect the position of the phone and adjusts its ranges automatically would be an improvement for our study.

We were only able to evaluate the incline parameter under predefined conditions, meaning that the level of incline was set before the user performs the activity on a tread mill. We have observed that our application is 90% accurate to estimate activity zone of the user for the elevation less than 3%. We also would like to set an environment for the experiment in which user performs different activity types on a ground with inconsistent slope. The GPS might help in registering the type of the slope and correlating

the slopes with the current activity, and we would be able to analyse the accuracy of our application with different slopes. Converting our application to one that adjusts itself and its activity zones based on the slope would be an improvement of our study.

In our study, we assumed that HR zones are stable and do not change from experiment to experiment. As we defined our activity zones during the learning phase of each experiment, we did not take the physical conditions of the user into consideration, which might be crucial to evaluate for the sake of our study. For instance, we believe that the time of the experiment may affect the HR zones because of the reasons given in Section 6.1.5. During long exercises the HR goes down but the HR varies during the day and is affected by additional work of the body like digesting. After eating, digestion process starts and lasts about 24 to 72 hours. Depending on the autonomic nervous system's command, the HR may be increased in an emergency situation (e.g. for elderly, the HR may go up due to decreased blood pressure as most of the blood being collected in organs involved in the process of digestion), or be decreased as the digest and rest command is given in order to save energy [80]. Such conditions have a direct effect on HR measurements. Other than that, each person has different HR values than each other when performing an activity depending on how efficient heart they have, meaning that a healthy heart works with less oxygen or uses less energy in comparison with an unhealthy heart [81]. Normal HR varies from person to person according to health of the person. However, it can also vary for the same person by age, physical condition or other parameters. In that case of variation, training phase needs to be repeated at a regular phase. This is also another matter to understand how often the user needs to re-take the training phase. We will evaluate such conditions in our future work.

Considering the point where we got by this study, we could specify that it is possible to get about the intensity of the user by using a mobile phone. After teaching the HR zones of the person to the system during the learning phase, the application is able to make an estimation of activity zone of the user by employing only the accelerometer sensor of the phone. We had the chance of evaluating our application only for the following activity types; slow walking (3.5 km/h), fast walking (5.5 km/h), slow running (5.5 km/h), and fast running (8.5 km/h). We would need to conduct more experiments in order to see whether our application works for other types of activities or if we need to employ extra sensors for the sake of accuracy, and to see how much of the internal (e.g. gyroscope, GPS) and the external sensors (e.g.

Fitbit, pedometer, other health-related sensors) could be integrated.

We talked about almost everything but we could not solve everything within the scope of this study. Activity and motion monitoring is a field of research where there are quite a lot of research groups are active and where novel applications reach the application store market almost on a frequent basis. Thus, it cannot be expected that our study which was conducted in a limited time frame could evaluate all the aspects.

## 8 Conclusion and Future Work

In this chapter, we present the concluding remarks on the study and share our recommendation for future work. First of all, it should be recalled that our purpose was to answer the question if it is possible to monitor activity level of the user corresponding to a heart rate zone. In other words, we have been out after seeing how much we can get about a user's PA by using only his smart phone without involving any external device during the application mode, but using only HR sensor for the learning phase in order to create a correlation between acceleration of the phone and HR measurement values of the person. In this term, we provided a state of the art overview in mobile-supported activity monitoring, performed a prototypical implementation and presented the evaluation of it.

Our study focused on correlating personal HR values to user activities. We observed a strong correlation between the accelerometer values registered by the smart phone and the HR values of the person doing a range of activities like slow walking, fast walking, slow running and fast running. Results show that we have a linear regression for the increase of accelerometer within each of these segments. As the intensity of the activity increases from slow walking to fast running, both the HR values of the person and acceleration in his smart phone get increased. As we presented in Linear Regression figures in Section 6.4, measured accelerometer value by the smart phone show an increase of 1 per 10 heart beats for walking activities, increase of 1,4 per 10 heart beats for running activities.

Our research further evaluated factors that affect accelerometer and HR measurements. We concentrated on the parameters which we found to be the most important to evaluate and identify a list of other parameters to be addressed in future work.

We covered a limited number of activity types. As stated before, optimizing an algorithm for activity detection is not the focus in this study. Our focus is on the understanding of the correlation of activity zone with accelerometer data. Our experience of activity identification shows that the range of activities could be extended to include e.g. cycling, skiing, climbing. Our experience has shown that accelerometer sensor is not enough for accurate detection of other activity types and thus we suggest to make use of other sensors from mobile phone like the gyroscope and the GPS. Work on activity detection is thus deferred to the outcome of research work from



other groups or to future work, as we focus on the activity zone.

Regarding the available applications in the market and research deployments that we touched upon in Section 5.2.1, we could state that our application differs from them in terms of functionality. We define activity zones based on the correlation between an activity type and HR of the user, while they are out after only activity detection or defining activity levels based on MET values, amount of the calorie burnt and user's characteristics (e.g. height, weight, etc.). We did not come across with a similar study focusing on the correlation as we did, by presenting a new concept called "activity zone", we could state that our study is the first of his kind in the area that checks the correlation between acceleration and health-related data which is HR data of the person in our case.

On the other hand, when having the bird's eye view of the whole picture in mobile supported activity monitoring, there are so many developments coming up there. We had the chance of running both Fitbit and Endomondo tracking applications together for the same training, and we ended up with two different results; Fitbit stated that the total calorie burn is 2.918 and the total distance that were run is 11.96 kms, while Endomondo gave the results stating the the user burnt 2100 calorie and ran for 20.1 kms. Our experience shows that the activity detection is a major starting point, after that the intensity of the activity can be judged properly explaining why Fitbit, focusing on steps, came up with different results than Endomondo, which uses the GPS to actually register distances. All this kind of applications are subject to further analysis. As a conclusion, we recommend to perform a comparative study of having a norm function of some of the activities. Depending on the desired outcome (e.g. calorie burn, fitness), other systems could get involved. As another future study, a combination of Fitbit and smart phone could be used in order to observe the difference in results in comparison with using only smart phone.

In Section 2.1 of this thesis, we performed an analysis of groups who might profit from the applicability of our ZE. The main groups were elderly people, people recovering after accidents, people with sedentary life style or people who just want to observe a certain intensity or each level of fitness will profit from ZE application. In a future scenario, it would be possible to add not only HR value but also other health related parameters to the study, and by the help of a smart phone as applied in our study, one could do further estimation.

We performed experiments on four types of activities with different slopes,

different positions of the mobile phone, and different phone types. Our experiments show that four types react very different with reporting accelerometer data, thus requiring additional training sequence. We further pointed out that the position of the phone is important to be taken into consideration. Therefore, we need to ensure that the position of the phone does not change when going from the training period into the operation period. Our further elements include the aspects of the specific impacts of a person doing the exercise and we are pointing out that the spread of HR is too big between different people. That's why, every person trying to use just a mobile phone sensor needs the training phase. The last part of our evaluation of the prototypical implementation pointed towards, the challenge is e.g power consumption and CPU usage. While we believe that this study provided insight into the correlation concept of acceleration and HR values of the person, there is still so much to do in the light of the improvements that we described as our future work [2] .

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bl&ots=6lzzoyzZBF&sig=6yewZxyD42eDn0MJVj5\_1bl1Glc&hl=tr&sa=X&ei=7hjcUsODBIG2hQee3IGgBA&ved=0CFAQ6AEwAw#v=onepage&q&f=false

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# Appendices

## Appendix A

<b>Use Case ID:</b>	[4]
<b>Use Case Name:</b>	Start the application mode
<b>Actors:</b>	End-user, ZE-GUI
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. End-user clicks the start button on the main screen</li> <li>2. ZE-GUI opens a new screen.</li> </ol>
<b>Trigger:</b>	End-user decides to run the application.
<b>Preconditions:</b>	The end user already accomplished the training phase.
<b>Post-conditions:</b>	N/A
<b>Normal Flow:</b>	ZE-GUI started
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	The application stops working unexpectedly due to a system failure or device failure
<b>Special Requirements:</b>	N/A
<b>Assumptions:</b>	N/A
<b>Notes and Issues:</b>	N/A

Figure 38: Use case : Start the application

<b>Use Case ID:</b>	[5]
<b>Use Case Name:</b>	Run the application mode
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. End-user clicks the Go button</li> <li>2. ZE-GUI starts ZE-Service</li> <li>3. ZE-Service starts processing the incoming data.</li> <li>4. ZE-Service logs the estimated activity zone and its duration into the history file.</li> <li>5. ZE-GUI shows the current activity zone on the screen.</li> </ol>
<b>Trigger:</b>	End-user decides to run the application.
<b>Preconditions:</b>	End-user is ready to perform some activities.
<b>Post-conditions:</b>	N/A
<b>Normal Flow:</b>	ZE-Service is already active
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	<ul style="list-style-type: none"> <li>- The application stops working unexpectedly due to a system failure or device failure</li> <li>- Accelerometer sensor stops working</li> </ul>
<b>Special Requirements:</b>	N/A
<b>Assumptions:</b>	N/A
<b>Notes and Issues:</b>	N/A

Figure 39: Use case : Run the application mode

<b>Use Case ID:</b>	[6]
<b>Use Case Name:</b>	View the history result
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. End-user clicks the history tab on the main screen</li> <li>2. ZE-GUI collects data from the log files</li> <li>3. ZE-GUI displays the results</li> </ol>
<b>Trigger:</b>	End-user decides to view past results.
<b>Preconditions:</b>	Log files are not empty.
<b>Post-conditions:</b>	N/A
<b>Normal Flow:</b>	History is shown seamlessly.
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	- Log files are not accessible.
<b>Special Requirements:</b>	N/A
<b>Assumptions:</b>	N/A
<b>Notes and Issues:</b>	N/A

Figure 40: Use case : View the history result

<b>Use Case ID:</b>	[7]
<b>Use Case Name:</b>	Quit the application
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. End-user clicks the HOME button available on any screens</li> <li>2. End user clicks the Quit button on the home screen</li> <li>3. ZE-GUI notifies ZE-Service about the request</li> <li>4. ZE-Service stops and exits</li> <li>5. ZE-GUI stops and exits.</li> </ol>
<b>Trigger:</b>	User wants to quit the application.
<b>Preconditions:</b>	ZE-GUI and ZE-SERVICE started
<b>Post-conditions:</b>	ZE-GUI and ZE-SERVICE stopped completely
<b>Normal Flow:</b>	ZE-GUI and ZE-SERVICE stopped completely
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	- Application stops working and quits with errors.
<b>Special Requirements:</b>	N/A
<b>Assumptions:</b>	N/A
<b>Notes and Issues:</b>	N/A

Figure 41: Use case : Quit the application

<b>Use Case ID:</b>	[8]
<b>Use Case Name:</b>	Start monitoring and logging the accelerometer values with HR values (Learning Phase)
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. ZE-Service starts listening to the accelerometer sensor of the mobile phone simultaneously with the external HR sensor.</li> <li>2. After logging the data into file for a dedicated period of time for walking, ZE-Service sends a message to ZE-GUI to notify the user about the process.</li> <li>3. ZE-GUI shows a warning message stating that training for the activity type "walking" is over and now same procedure will repeat for the activity "running".</li> <li>4. ZE-Service completes the training phase and informs ZE-GUI about it.</li> <li>5. ZE-GUI goes back to Home screen with the following notification; "Training has been done successfully!"</li> </ol>
<b>Trigger:</b>	Training mode is necessary and end-user clicks the run button on the training screen.
<b>Preconditions:</b>	N/A
<b>Post-conditions:</b>	N/A
<b>Normal Flow:</b>	Training mode is completed successfully
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	<ul style="list-style-type: none"> <li>- Bluetooth connection fails.</li> </ul>
<b>Special Requirements:</b>	<ul style="list-style-type: none"> <li>- External Zephyr sensor is worn as expected.</li> <li>- Bluetooth of the mobile phone is on</li> </ul>
<b>Assumptions:</b>	<ul style="list-style-type: none"> <li>- Sensors are on working seamlessly.</li> <li>- There is no problem with accessing to log files.</li> </ul>
<b>Notes and Issues:</b>	N/A

Figure 42: Use case : Start monitoring and logging operations

<b>Use Case ID:</b>	[9]
<b>Use Case Name:</b>	Stop Learning Phase
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. After logging for last activity is done, ZE-Service completes the training phase and informs ZE-GUI about it.</li> <li>2. Meanwhile ZE-Service starts to process signal analysis phase.</li> <li>3. ZE-Service defines the activity zones for each activity type.</li> <li>4. When all signal analysis is over, ZE-GUI goes back to Home screen with the following notification; "Training has been done successfully!"</li> </ol>
<b>Trigger:</b>	Learning phase is over.
<b>Preconditions:</b>	N/A
<b>Post-conditions:</b>	N/A
<b>Normal Flow:</b>	Training mode is completed successfully
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	- Writing to log files fails.
<b>Special Requirements:</b>	N/A
<b>Assumptions:</b>	- There is no problem with accessing to log files.
<b>Notes and Issues:</b>	N/A

Figure 43: Use case : Start the application

<b>Use Case ID:</b>	[10]
<b>Use Case Name:</b>	Start the application mode
<b>Actors:</b>	End-user, ZE-GUI, ZE-Service
<b>Description:</b>	<ol style="list-style-type: none"> <li>1. ZE-Service starts signal analysis of incoming accelerometer data</li> <li>2. By the help of information created during the learning phase, the current activity of the person is determined for each period of 5 seconds</li> <li>3. ZE-GUI shows the current activity zone of the person on the screen.</li> </ol>
<b>Trigger:</b>	User starts the application mode.
<b>Preconditions:</b>	N/A
<b>Post-conditions:</b>	N/A
<b>Normal Flow:</b>	Logging and activity zone estimation operations get in progress until the user stops the application.
<b>Alternative Flows:</b>	N/A
<b>Exceptions:</b>	- The application stops working unexpectedly due to a system failure or device failure
<b>Special Requirements:</b>	N/A
<b>Assumptions:</b>	N/A
<b>Notes and Issues:</b>	N/A

Figure 44: Use case : Start the application



## Appendix B

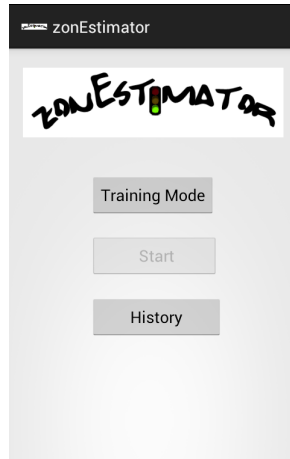


Figure 45: Screen shot of the Starting screen

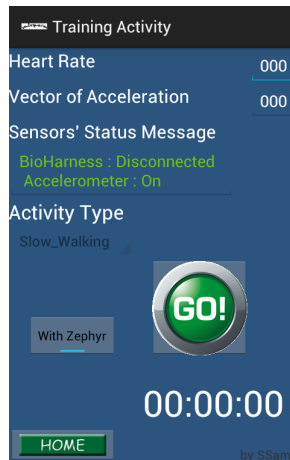


Figure 46: Screen shot of the Training screen

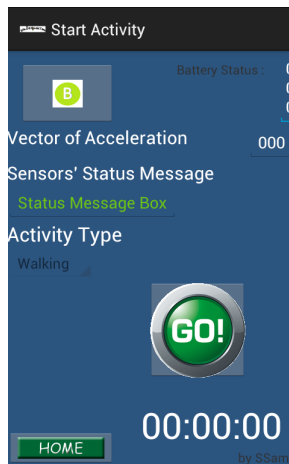


Figure 47: Screen shot of the Run mode

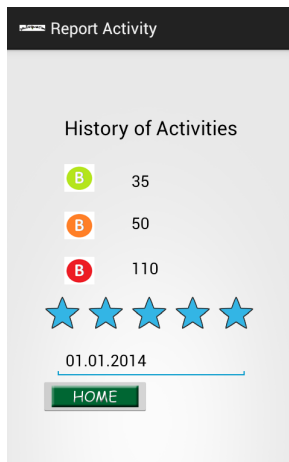


Figure 48: Screen shot of the Reporting screen

## Appendix C

```
1 private float [] highPass(float x, float y, float z) {
3     //Log.i("highPassCalled : " , "highPassCalled");
    float [] hfilteredValues = new float [3];
5     //Log.i("firstRound : " , ""+firstRound);
    //Log.i("incoming x,y,z vals:" , ""+ x +"," + y +"," + z);
7     if(firstRound == true)
    { gravityvalues = new float [3];
9         gravityvalues [0] = alpha *1 + (1 - alpha) * x;
        gravityvalues [1] = alpha * 1 + (1 - alpha) * y;
11        gravityvalues [2] = alpha * 1 + (1 - alpha) * z;
        //Log.i("calculating gravityvalues " , ""+gravityvalues [0]
+ " , " + gravityvalues [1] + " , " +gravityvalues [2]);
13        hfilteredValues [0] = x - gravityvalues [0];
        hfilteredValues [1] = y - gravityvalues [1];
15        hfilteredValues [2] = z - gravityvalues [2];
        firstRound = false;
17        //Log.i("about to exit . gravityvalues : " , "
gravityvalues x:" + gravityvalues [0]);
    }
19    else
    {
21        //Log.i("prev recorded gravityvalues : " , "gravityvalues
x:" + gravityvalues [0]);
        gravityvalues [0] =alpha * gravityvalues [0]+(1 - alpha) * x
;
23        gravityvalues [1] =alpha * gravityvalues [1] +(1 - alpha) *
y;
        gravityvalues [2] =alpha * gravityvalues [2] +(1 - alpha) *
z;
25        //Log.i("calculating gravityvalues " , ""+gravityvalues [0]
+ " , " + gravityvalues [1] + " , " +gravityvalues [2]);
        hfilteredValues [0] = x - gravityvalues [0];
27        hfilteredValues [1] = y - gravityvalues [1];
        hfilteredValues [2] = z - gravityvalues [2];
29        //Log.i("about to exit . gravityvalues : " , "
gravityvalues x:" + gravityvalues [0]);
    }
31    //Log.i("highPassCalled : " , "highPassCalled x:" +
hfilteredValues [0]);
    return hfilteredValues;
33 }
```

Listing 1 : High Pass Filter