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Context Aware Reminder System

Activity Recognition Using Smartphone Accelerometer and Gyroscope Sensors Supporting Context-Based Reminder Systems

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ABSTRACT

Context. Reminder system offers flexibility in daily life activities and assists to be independent. The reminder system not only helps reminding daily life activities, but also serves to a great extent for the people who deal with health care issues. For example, a health supervisor who monitors people with different health related problems like people with disabilities or mild dementia. Traditional reminders which are based on a set of defined activities are not enough to address the necessity in a wider context. To make the reminder more flexible, the user's current activities or contexts are needed to be considered. To recognize user's current activity, different types of sensors can be used. These sensors are available in Smartphone which can assist in building a more contextual reminder system.

Objectives. To make a reminder context based, it is important to identify the context and also user's activities are needed to be recognized in a particular moment. Keeping this notion in mind, this research aims to understand the relevant context and activities, identify an effective way to recognize user's three different activities (drinking, walking and jogging) using Smartphone sensors (accelerometer and gyroscope) and propose a model to use the properties of the identification of the activity recognition.

Methods. This research combined a survey and interview with an exploratory Smartphone sensor experiment to recognize user's activity. An online survey was conducted with 29 participants and interviews were held in cooperation with the Karlskrona Municipality. Four elderly people participated in the interview. For the experiment, three different user activity data were collected using Smartphone sensors and analyzed to identify the pattern for different activities. Moreover, a model is proposed to exploit the properties of the activity pattern. The performance of the proposed model was evaluated using machine learning tool, WEKA.

Results. Survey and interviews helped to understand the important activities of daily living which can be considered to design the reminder system, how and when it should be used. For instance, most of the participants in the survey are used to using some sort of reminder system, most of them use a Smartphone, and one of the most important tasks they forget is to take their medicine. These findings helped in experiment. However, from the experiment, different patterns have been observed for three different activities. For walking and jogging, the pattern is discrete. On the other hand, for drinking activity, the pattern is complex and sometimes can overlap with other activities or can get noisy.

Conclusions. Survey, interviews and the background study provided a set of evidences fostering reminder system based on users' activity is essential in daily life. A large number of Smartphone users promoted this research to select a Smartphone based on sensors to identify users' activity which aims to develop an activity based reminder system. The study was to identify the data pattern by applying some simple mathematical calculations in recorded Smartphone sensors (accelerometer and gyroscope) data. The approach evaluated with 99% accuracy in the experimental data. However, the study concluded by proposing a model to use the properties of the identification of the activities and developing a prototype of a reminder system. This study performed preliminary tests on the model, but there is a need for further empirical validation and verification of the model.

Keywords: accelerometer, gyroscope, Smartphone sensor, reminder system, activity recognition.

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Qutub and Saifullah

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ACRONYMS

ADT	Android Development Tools
ANP	Adjacent Next Point
APNP	Average of PNP
APP	Adjacent Previous Point
PP	Peak Point
PNP	Peak Neighborhood Points
SPNP	Standard Deviation of PNP
STD	Standard Deviation
SDK	Software Development Kit
RFID	Radio-frequency Identification

1 INTRODUCTION

Living independently is a social and economic challenge for promotion of a healthier society [1]. To adhere to be independent, reminder system can offer services to assist to make life easier [2]. Different people like businessmen, lawyers, students and people who need care at home like persons with disabilities or mild dementia need a reminder system [3]. Reminder systems can address the necessities of the users to remind performing pending tasks on time.

Traditional reminder system (e.g., paper or electronic) prompts based on a set of defined activities which have inflexibility of skipping wider context of necessity. These systems can be irritating and annoying over time due to the nonsequential nature of human activities or overlapping within multiple activities. For instance, a reminder prompts while the user is busy with talking on the phone. Considering these phenomena, user‘s current activities or contexts are needed to be taken into account to make the reminder system flexible.

The system which considers current situation or context are known as context-aware systems [3]. In the research point of view, ―Context" demonstrates a system where a computer can sense their surrounding environments, customize functionalities based on the acquired information from the surroundings and act in response [2]. Applications, which are context-aware, are capable to evaluate user requirements, customize according to their profile and provide personalized service and information that are relevant to user context [3].

Context-aware system aims to understand the condition of a user with the presence of contexts and serve accordingly [4]. To understand the situation of a user with the presence of contexts, user‘s activities are monitored by attaching different wearable sensors in different parts of the body. Using the sensors, activity information is acquired. The acquired information then analyzed and processed [1]. In recent years, there has been much advancement in the research of users‘ activity recognition based on context aware system [4]. These wearable sensors, used in users‘ activity recognition, are embedded in Smartphone [1], which have the potential to be used as an effective sensor tool to identify the activity that the Smartphone user is currently engaged in.

Smartphones provide advanced functionality beyond voice and message services [1]. Their widespread usage is advantageous for the realization of context aware systems. Recent Smartphone are equipped with a variety of sensors such as accelerometer, gyroscope, GPS, microphone, image sensor, light sensor, proximity sensor, temperature and pressure sensors etc. [4][5]. These sensors can be an effective tool to understand the user‘s context which can lead to develop context-aware applications. During the last decade, in different researches [5][6][7][8] increasing interest in this research area has been observed. In these researches, different sensors like accelerometer, gyroscope, pressure, and magnetometer are used to identify the user‘s activity, for example, walking, jogging, standing up, sitting down, falling, and climbing up and down stairs. In this study, two Smartphone embedded sensors (accelerometer and gyroscope) have been used to identify user‘s activity by mining the sensor data.

In this study, three activities have been selected - walking, jogging, and drinking. The aim was to recognize these activities through Smartphone sensors (accelerometer and gyroscope) data. The keen interest of this study was to observe if there are some identical unique patterns for each activity in recorded sensor data. These patterns could then be used as a measurement scale to identify the selected activities by using the Smartphone. The raw inertial sensor data was collected with the help of 12 participants. Then features extracted by applying mathematical calculations on the raw data to formulate a pattern for the corresponding activity. The results concluded by suggesting a range of values for each activity. The accuracy of the proposed approach measured by using C4.5 classifiers (the WEKA implementation is J48). Finally, a prototype of an Android mobile application has been developed following the proposed activity recognition model.

1.1 Aims and Objectives

The main aims and objectives of the study are to develop a context aware reminder system based on different human activities. We have selected three different activities: walking, jogging and drinking.

- Identify different body movements (walking, jogging and drinking) of concern for reminder systems and measure these activities with accelerometer and gyroscope sensors.
- Design a reminder system to support users based on previously identified accelerometer and gyroscope sensor's data measurement patterns connected to situations of relevance.

1.2 Expected Outcome

The results of the study can help to identify user's activity which can be used to develop a context aware reminder system. The expected outcomes of the study are as follows:

- The activities people forget to perform in daily life and the types of reminder system people need.
- Collecting data on human behavior (walking, jogging and drinking) by Smartphone sensors (accelerometer and gyroscope).
- An implementation of a context aware reminder system.

1.3 Research Questions

The following research questions were posed:

RQ1: Which situations can be supported by the reminder systems?
RQ2:

a. How can we measure activities (walking, jogging and drinking) with technology (Smartphone accelerometer and gyroscope)?
b. How can we use the measurement results to automate reminder to the users?

RQ3: How can we design reminders using Smartphone to be a support for the users?

1.4 Thesis outlines

We have designed the structure of our thesis in nine chapters.

Chapter 2 presents the background and related works in the area of activity recognition. The literature review is also described in this chapter, which is conducted to obtain the information about the background and related works.

Chapter 3 presents a general description of the technologies which have been used in this study.

Chapter 4 presents the methodologies have been used in this study.

Chapter 5 presents the process and the results of survey and interview, which is for answering the research question 1.

Chapter 6 presents a description of the experiment and evaluation, which is for answering the research question 2.

Chapter 7 presents a description of the implemented prototype of a reminder system which is for answering research question 3.

Chapter 8 presents the discussion and validity threats of the study.

Chapter 9 presents the contribution of the thesis along with some possible future works.

2 BACKGROUND AND RELATED WORK

In this chapter we have described the background of our study in section 2.2 and related works in section 2.3. To obtain the information about background and related works we performed the literature review which is described as follows.

2.1 Literature Review

The literature review is basic and an important task for any research to get the relevant information on particular research topic [9]. The literature review recapitulates all related research in a particular research area [9]. The gap can be identified in that research area and it can be informed how much the previous researches have reached. It also helps to identify the information and necessary methods and techniques which have been used in this research area.

The aim of the literature review of this study was to know about the previous experiments which have been done in the area of activity recognition using Smartphone sensors (accelerometer and gyroscope).

2.1.1 Search strategy

In order to search relevant resources, the following steps have been followed:

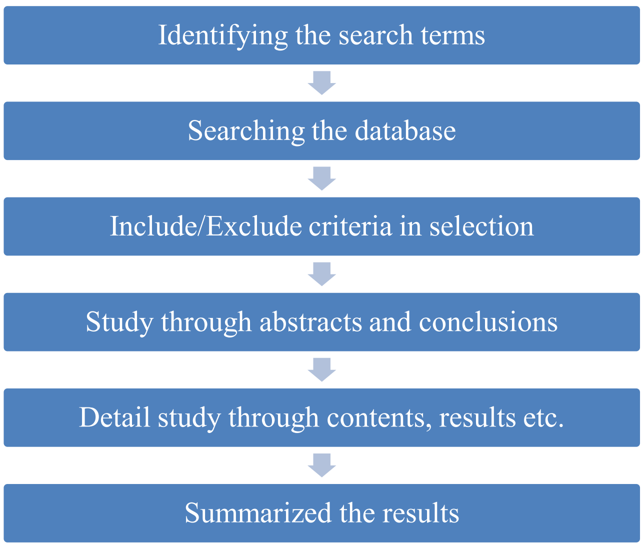

Figure 1: Steps of the literature review

2.1.2 Identify the search terms

The following steps were followed to construct the search terms:

- Identified the search terms related to our research domain
- Used synonyms and alternate keywords of the search terms
- Boolean AND and OR operators were used with the synonyms and alternate keywords of the search terms.

The search terms which have been used are listed below:

Search Terms: Smartphone, accelerometer, gyroscope, activity recognition, reminder system.

Synonym: mobile, mobile sensors, smart reminder system, reminder systems.

2.1.3 Electronic database

The following different library databases were inspected for searching the pertinent literature.

- ACM
- IEEE Xplore
- Springer Link
- Google Scholar

2.1.4 Study Selection Criteria

After selecting the electronic library databases, inclusion and exclusion criteria were defined. Inclusion and exclusion criteria refer to the rules by which relevant and irrelevant articles can be differentiated and those articles can be included or excluded from the study.

2.1.5 Inclusion Criteria

- The title and the abstract of the article match with the problem domain.
- The article available in full text.
- The language of the article is English.

2.1.6 Exclusion Criteria

- The full text article is not available.
- The language of the article is not in English.
- The sensors used in the studies which are not related to our research domain.

Inclusion and Exclusion criteria were applied at the following different levels:

- Title/Abstract
- Introduction/Conclusion/Future work
- Materials and Methods/Experiments
- Results and Discussion

2.1.7 Conducting Review

In the searched articles, the inclusion and exclusion criteria were implemented. Then the resultant articles were reviewed by studying abstract, introduction and conclusion. At the end, the full text were studied which were relevant and useful for our research.

2.2 Background

In modern society, people are overwhelmed by enough tasks which are waiting to be done. Tasks can be of many types, such as meeting at work, shopping, visiting doctors, taking medicine, bill payments, taking care of kids and elderly people and many other things. Humans are forgetful, so they need such a system which can remind them of their task in time. The reminder is not a new concept; it is from the beginning of the human civilization. Reminder systems remind users the pending work list in time. Personal task reminders are essential for modern people, which can remind them of their tasks at the specific situation. Traditional paper based reminder system is still effective, but they cannot be set up efficiently. On the other hand, the electronic reminder system is more efficient, but they are based on the calendar and time [10]. In many situations, tasks are related to performing in a specific location, such as shopping. Normally, task can be classified into two categories, such as Time priority tasks and Location priority tasks [10]. Time priority tasks should be carried out at specific times. For example, every day taking medicine at 7:00 a.m. We can set the alarm by ourselves to get the reminder everyday at 7:00 a.m. On the other hand, for a location priority task, we can set the task list and when we will be near the specific location the reminder system will trigger on with the task list. For example, purchasing specific products from the specific shopping mall [10].

Day by day users' demands are getting smarter; that they need such a system which can suggest the user what should they perform depending on the surrounding environment. On the other hand it is also not expected to get the reminder after performing the task, but better is to get the reminder if the task is not performed. The smart reminder system should understand whether the task has been done or not. If the task has been performed reminder system should not remind the user for the specific task. For example, someone needs medicine every day at around 8:00 to 9:00 am. If he/she takes the medicine on time, reminder system does not need to remind him/her for the medicine. Most people are used to do exercises (like walking and jogging) in their daily life for better health. During our physical exercise we lose water from our body. So we should drink sufficient amount of water after the exercise. If the reminder system can recognize the drinking activity, whether he/she performed after the exercise, then the reminder system can generate a reminder based on his/her activity. This type of reminder system can be named as context-based reminder system. To build a context-based reminder system, activity recognition is most important. To identify user activity, many modern types of equipment can be used, such as camera, different type of sensors, like accelerometer, gyroscope and others. Currently accelerometer sensor is widely used for the activity recognition [11]. A Smartphone is a good device to use different sensors like accelerometer and gyroscope effectively for the activity recognition. We can use Smartphone to record user activity data to get the pattern in data to identify the user specific activity.

Pattern recognition is not a new concept, but people have been studying patterns in data ever since at the early phase of human life. Not only human, every living being seeks pattern in their daily life. Farmers look for patterns in crop growth, hunters look for patterns in animal migration behavior, politicians seek patterns in voter sentiment, doctors seek patterns in disease, and meteorologists seek patterns in climate changing. One scientist‘s job is to make data as meaningful as to find out the patterns that rule how the physical world actually works and encapsulate them in theories that can be used for predicting what will happen in new circumstances [12].

Data mining is about looking for patterns in data. In this manner, text mining is about looking for patterns in text: It is the process of analyzing text to extract information that is useful for particular purposes [12]. Data mining is defined as the process of discovering patterns in data. The procedure must be automatic or semiautomatic. The pattern identifying must be significant in that they lead to some advantage, usually an economic one. The data invariably present in substantial quantities [12].

Many different arising application domains have been introduced new constraints and methods for data mining. One such application domain is identifying the activity and recognition in smart environments. Now-a-days, people aging is increasing worldwide because of medical advances, better nutrition, sanitation, health care, education and economic well being and so on, which rising demand for in-home monitoring. That‘s why smart environments have attracted many researchers from different subject areas. A smart environment is an environment which is equipped with different types of sensors, such as infrared motion sensors, RFID tags, power-line controllers and others. The sensor data are obtained from different sensors; these data is mined and analyzed to detect the residents‘ activities. Recognizing residents‘ daily activities can greatly help in providing security and more importantly in remote health monitoring of elderly, or people with disabilities. It also can determine when the resident needs assistance or turn on an alarm if needed [13].

2.3 Related Work

Sensor based activity recognition has got a lot of attention in the research field. Some of the research works have been mentioned in this section. These related works have been extracted from the literature review.

Hoseini-Tabatabaei et al [14], presented a survey on Smartphone-based systems for opportunistic user context recognition. Mobile-centric context recognition system strength are rising day by day because of continuous increasing of computation and memory capabilities of mobile phone, which are able to sense and analyze the context of the carrier so as to provide an appropriate level of service. Several open challenges are discussed and possible ways to increase the capabilities of the state-of-the-art approach.

Borazio and Van Laerhoven [15], presented the capabilities of the mobile devices can recognize user activities. They examine the statistical information of the time use survey database, combined with mobile acceleration data to determine 11 activities. They showed how sensor data and time survey information can be merged, and they have evaluated their approach on different users with several days.

Lin and Hung [10], they developed a location-based personal task reminder application. This application is developed for Android-based Smartphones and tablets which can work effectively in both indoor and outdoor environments. They mainly focused on GPS technology to distinguish from state-of-the-art approach; they took the advantage of IEEE 802.11 WLAN infrastructure to complement the ―blind spots” of GPS location sensing. If WLAN infrastructure is available, they demanded their work is a foundation of location-based services can be enhanced to be used in many other circumstances, like guiding in location-based learning, public transportation systems, and even caring of the Dementia residents.

In this paper [16], accelerometers and pressure sensing is used to improve activity recognition on Smartphone. They did an experiment using a Smartphone on four activities – standing up, jogging, and walking up and down stairs. Their outcome suggested that a detection of a change in pressure in the Smartphone‘s sensor can be an indication of user‘s activity and attitude. The pressure sensor‘s data can improve the performance of activity recognition together with accelerometer sensor data.

Brezmes et al. [5], implemented a real-time classification system using Smartphone‘s accelerometer, to identify basic human movements like walking, standing up, sitting down, falling, climbing up and down stairs. According to the paper, there have training phase where sensor data is stored and then classified using k-nearest neighbor algorithm. Then the recognition of certain activity depends on the Euclidean distance of the new data compared with previously stored data which has already been classified.

Kwapisz et al. [6], evaluated a system which identifies physical activity a user is performing using phone-based accelerometers. To implement their system they have collected data from the users for their daily activities like sitting, standing, walking, jogging and climbing stairs. They summarized the user activity for 10 seconds and from the data they induced a model to recognize a user‘s activity.

Shoaib et al. [7], investigated the role of three different Smartphone sensors, accelerometer, magnetometer and gyroscope, to recognize activity. They used seven commonly used classifiers with time domain features. They evaluated in four body positions: right jeans pocket, belt, right arm, and right wrist. They considered six activities to investigate - walking, running, sitting, standing, walking upstairs and downstairs. They collected data at the rate of 50 samples per second. They have shown that, accelerometer and gyroscope complement each other in the process of activity recognition and in some cases; individual sensor performs better in different situations. For example, gyroscope recognized well the walking upstairs activity, whereas accelerometer recognized standing activity better. On the other hand, the performance of a magnetometer was poor or needs to be improved in the process of activity recognition. They concluded that these sensors role can hardly be described by an exact generic statement for all situations in the process of activity recognition. Based on their evaluation, the role of the sensors depends on some factors: the position of the Smartphone, the classifiers are being used, the selected activity etc.

Thammasat E. [8], conducted statistical analysis to recognize the walking, jogging and running activities using Smartphone accelerometer. They applied statistical analysis: narrative statistics, variance analysis, T-test and F-test. Their study demonstrated that the statistical method has significance to distinguish the walking activity from jogging and running activity, but not for only jogging and running for their selected subject. They have suggested that different results can be found in case of different subjects.

To summarize, in previous studies Smartphone accelerometer, gyroscope, magnetometer, pressure sensing have been used to recognize a user's activity. They have tried to recognize different activities like standing up, sitting down, falling, walking, jogging, running, walking up and down stairs. Different methods have been used in their research, in a study, they have applied statistical analysis and in another, they have used different classifiers with time domain features.

In this study, we aimed to develop an application that would be very helpful in specific situations i.e. health care. We aimed to recognize three different activities: walking, jogging and drinking using Smartphone accelerometer and gyroscope sensors. There have some previous researches on walking and jogging, we aimed to add a new and complex activity: drinking. We wanted to find a common approach to follow and identify these three activities.

3 TECHNOLOGICAL OVERVIEW

This chapter contains the information about the technologies which have been used in this thesis – Smartphone‘s different sensors like accelerometer, gyroscope, GPS etc. Google‘s Android platform has also been described, which is used to develop applications in Smartphone using the Smartphone sensors.

3.1 Reminder system

Reminder system is a system, which can be telephones, color-coding, computerized reminders or paper-based reminders such as letters and postcards, used to prompt or aid the memory [17]. Reminder strategies are used in daily basis such as diaries, personal notes, calendars, sticky notes, or visual reminders to support people, especially elderly people to remind and prompt them to perform their tasks at the appropriate time and place [18]. The elderly people can benefit more by using the Reminder system to manage their daily life. Reminders are needed in different aspects of daily life, for example, the necessary tools we need to keep with us (such as a bus pass), or meetings/appointments details, or any specific tasks for the day. At home, young and old people can use the reminder system to get the reminder to turn off their machines or take medicines on time [19].

Figure 2: Examples of some reminder systems [20]

Reminder systems are playing an important role in the assisted living solutions in recent days. Assisted Living Technology deals with electronic reminders and notifications at home environment to improve activeness and to be able to enjoy independent leisure activities at home [19].

3.2 Smartphone Technology

According to the definition of the Oxford dictionary, –*Smartphone is a mobile phone that is able to perform many of the functions of a computer, typically having a relatively large screen and an operating system capable of running general-purpose applications.*" Smartphone or the latest mobile phones are rapidly merging in people‘s life not only as a communication device but also as the central computing device [21].

Nowadays, the mobile phone has become a must have gadget in daily life. It is used everywhere and every time for communication, entertainment or for different health and wellness related applications. Smartphones are more powerful and rich in features as well as less costly due to advances made in various technological domains [22]. Besides primary use of personal communication and entertainment, it can also widely used in various health and wellness monitoring applications [23]. Enhanced computing, powerful embedded system, multi-touch interface, multimedia, empowering user friendly design and intuitive usage results in an easy to use Smartphone for everyone even by the disabled and the elderly people [24].

Today‘s Smartphone is not only a communication and computing and mobile device; it is also embedded with different sensors. Some of the common sensors used in Smartphone are - accelerometer, gyroscope, digital compass, proximity sensor, GPS, microphone, camera etc. These sensors enable applications in Smartphone across different domains, like healthcare [25], safety, environmental monitoring [26] etc., and encourages a new research area called mobile phone sensing [21]. Some of the areas which make use of Smartphone sensors are shown in the following figure [27]:

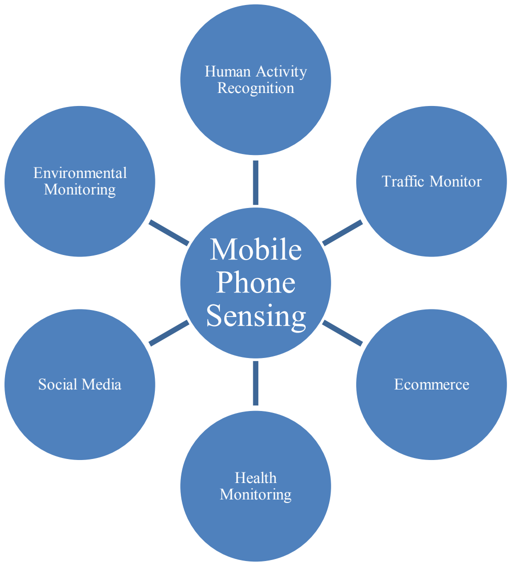

Figure 3: Areas leveraging Smartphone sensors

Some of the sensor‘s descriptions are in the following sections:

3.2.1 Accelerometer

Most of the new Smartphone‘s are assembled by embedding triaxial accelerometer sensor. An accelerometer sensor measures the acceleration in three spatial dimensions (x, y, z). This sensor is also capable of detecting the orientation of the device; either the device is in a horizontal or a vertical position. Initially, this sensor was included in the Smartphone to enable automatic screen rotation and support advanced game play. But this sensor also has many other applications. If we can recognize user‘s activity using the information provided by accelerometer sensor, many useful applications can be built by using this information. For example, in the healthcare system, if we can recognize a user‘s activity like walking, jogging or drinking, we can automatically monitor a user‘s activity level related to their health care issue. We can generate reports based on their activity and we can send those data to the users or physicians to monitor if the users are getting an adequate amount of exercises or consuming a sufficient level of minerals. Thus the users can get a feedback or alert of their health status which could be used to encourage healthy practices in daily life [6].

Data	Description
X	Acceleration value of X axis
Y	Acceleration value of Y axis
Z	Acceleration value of Z axis

Table 1: The axis values of the accelerometer sensor

In the experimental part of this study, Samsung galaxy S4 Smartphone has been used which is embedded by LSM330 3D accelerometer. According to the documentation [28], the sensor can be used to impact recognition, motion activated functions, vibration monitoring, free fall and 6D orientation detection. It also consumes less power (0.25 mA).

In practical orientation (when the device laying flat on the table), this sensor works in the following ways:

Value	When
The X axis value is positive	Move the device on the left side
The Y axis value is positive	Move the device on the bottom
The Z axis value is equal to A + 9.81, which corresponds to the acceleration of the device (+A m/s^2) minus the force of gravity (-9.81 m/s^2).	Move the device toward the sky with an acceleration of A m/s^2

Table 2: Axis value of device movement

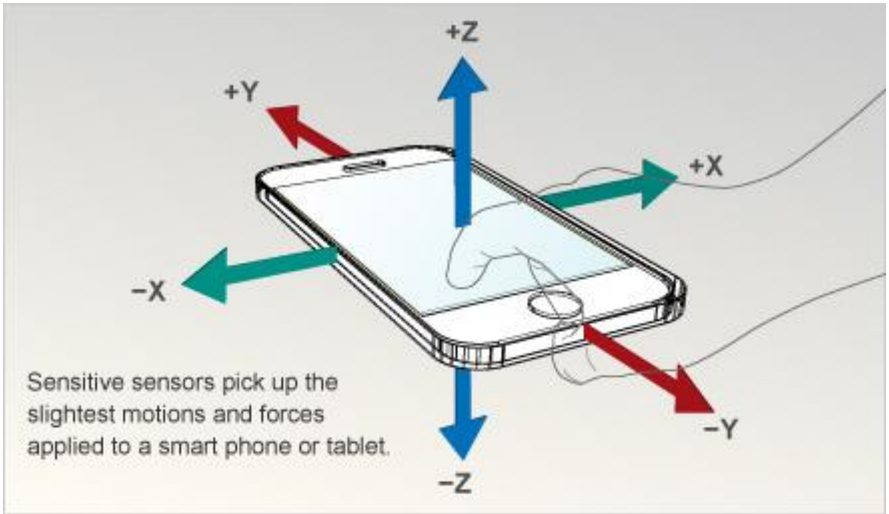

Figure 4: The axis of the accelerometer sensor [29]

3.2.2 Gyroscope

A gyroscope sensor is used for measuring or maintaining orientation of a device. This sensor works based on the principles of angular momentum. It measures rotation rate of a device in rad/s around the devices each of the three physical axes (x, y, and z axis).

Rotation counts positive when the device rotate in the counterclockwise direction [30]. In Smartphone and tablet PCs, gyroscopic sensors are used for finding the position and orientation of the device, in the navigation and gesture recognition systems.

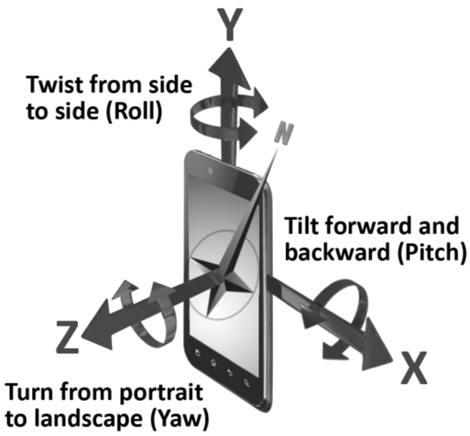

Figure 5: The axis of gyroscope sensor in Smartphone [31]

Gyroscope sensor, along with an accelerometer, allows the Smartphone or tablet PCs to sense motion on six axes – left, right, up, down, forward and backward, as well as roll, pitch and yaw rotations which allow the device‘s accurate motion sensing ability [32].

Data	**Description**
Yaw	Rotation angle of Yaw axis
Pitch	Rotation angle of Pitch axis
Roll	Rotation angle of Roll axis

Table 3: The gyroscope sensor axis value description

3.2.3 GPS

The Global Positioning System (GPS) is a global navigation satellite system. In other words, GPS is a space based radio navigation system that provides accurate location and timing services to anyone with a GPS receiver. It was developed and deployed by the US Department of Defense and maintained by the US Air Force. This service, made available to civilians without charge in 1996 for navigation purposes. It is functional anywhere in the world and can support an unlimited number of users [33].

Most of today‘s Smartphones are equipped with fully functional GPS receivers and supporting applications.

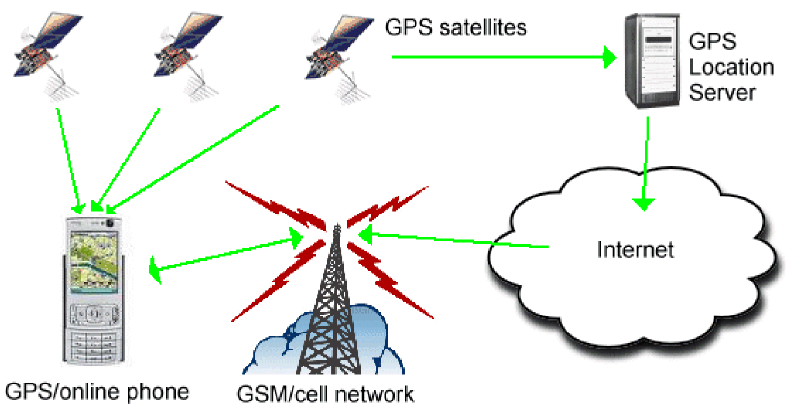

Figure 6: GPS network [34]

3.2.4 Android Platform

Android is an open-source platform announced by Google. According to the Android's official page, more than a billion phones and tablets are powered by Android around the world. It is composed by the operating system, the middleware and key applications. Android is available as open source software under the Apache License.

Android is a distribution of Linux that includes a Java Virtual Machine (JVM), with Java being the preferred programming language for most Android applications. For the developer, the Android has a Software Development Kit (SDK) which includes a debugger, libraries, a handset emulator, documentation, sample code, and tutorials. Android has integrated a development environment in Eclipse IDE using the Android Development Tools (ADT) plug-in. The ADT plug-in includes an Android emulator that allows for the simulation of the developed applications in the IDE. As an open source platform, Android enables developers to create applications that utilize the features the mobile device and customize according to the needs of the consumer. Android allows for the combination of information from the web with core features of the phone such as the camera function and text messaging [35].

4 RESEARCH METHODOLOGY

The research strategies used in this thesis are survey and interview followed by an experiment. Survey and interview were conducted first to know about the daily life activities that can be assisted by reminder system. To know about different context in daily life, it was needed to know the responses from different persons which led us to conduct surveys and interview which have been described in Chapter 5.

An experiment was conducted to identify the pattern of three different human activities, namely walking, jogging and drinking by using Smartphone sensors like accelerometer and gyroscope. To understand the behavior of the Smartphone sensors, it was needed to get streaming data from those sensors while the activity is done. Through the experiment we achieved this objective. Then the data patterns were studied to find key differences in the sensors‘ output data for distinguishing and recognizing each of the aforementioned activities. The experimental method has been described in detail in Chapter 6.

Finally an android based mobile application was developed to implement the knowledge acquired from the experimental data analysis to enable the Smartphone to recognize one of the three activities and set an appropriate reminder.

The following table presents the mapping between research questions, their purpose and the corresponding chapters where the research questions have been answered.

Research Question	Purpose	Answering Section
RQ1: Which situations can be supported by the reminder systems?	To know which situations and what types of the reminders people need in their daily life activities.	Chapter 5
RQ2 (a): How can we measure activities (walking, jogging and drinking) with technology (Smartphone accelerometer and gyroscope)?	To identify patterns of different human activities from the collected data by Smartphone sensors.	Chapter 6: section 6.1 to 6.5
RQ2 (b): How can we use the measurement‘s results to automate a reminder to the users?	To propose an activity recognition model.	Chapter 6: section 6.6
RQ3: How can we design reminders using Smartphone to be a support for the users?	To develop a prototype by using our proposed activity recognition model.	Chapter 7

Table 4: Research questions, their purpose and their answering sections

5 SURVEY AND INTERVIEW

We have conducted surveys and interviews to answer the research question 1.

5.1 Survey

The survey is the technique to collect data and get feedback by asking questions from a number of people who have the desired information [36]. This chapter depicts the survey process and the information gathered from the survey during our study. The main objective of the survey was to collect data about daily life activities where the user needs a reminder. Another purpose of our survey is to get familiar with the preferences and interest of users towards electronic devices and state of the art technologies. Details of the survey are given below:

5.1.1 Survey Process

We followed the following steps for conducting the survey:

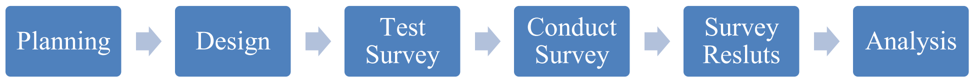

Figure 7: Survey Process

5.1.2 Planning and Design

The purpose of our survey has been to collect data on daily life activities and to gather knowledge on the requirement of reminders for people in everyday life. To acquire this information, we asked questions about the technology that is in use at present and the way it should evolve and be needed in the future while the reminder is required the most.

To serve the purpose, we conducted a literature review and discussed with our supervisor to finalize our questionnaire both in English and Swedish to make it convenient for everyone participating in the survey. We tried to make the questionnaire short, precise and easy to understand for the general public.

The following issues we have considered while designing the survey questionnaire–

- Simple and short questions
- Easy to read and easy to answer questions
- Two versions of questionnaire, in English and Swedish

The questionnaire is attached in Appendix A.

5.1.3 Test Survey

To start our survey, we conducted a test survey to get some response and comments about the questionnaire. This helped us in finding out the errors made in the questionnaire and some important issues which we have missed initially. We also tried to ensure the ease of readability of the questionnaire. Finally, we checked if the questionnaire meets the purpose of the survey.

After conducting test surveys, we made an amendment in the questionnaire like removed errors, changed order to make the questions easy to answer, addition of some more points, and changing the language of the questions. Finally, we sent the final survey questionnaire to 50 different people.

5.1.4 Conducting Survey

The final questionnaire has been sent to 50 different people. We received responses from 29 people.

5.1.5 Survey Results

We have conducted surveys on 29 participants of different age and professions. The purpose of the survey was to attain knowledge on their daily life activities, their preferences during usage of electronic devices in daily life, participant‘s interest in reminder system in everyday life.

The questionnaire has different parts, the first part required the participants to inform their age, and then it required them to let us know how frequently they use the reminder system on their electronic devices or whether they do not use it all. At the end, we collected information on what types of reminder they need, when mostly they need the reminder and how frequent.

The results of the survey are given in details in Appendix B.

5.1.6 Survey Analysis

Here is the summary of the result of the survey:

- Most of the participants use reminder system.
- Most of the participants use a Smartphone and more than half of them use calendar system in their Smartphone.
- One-third of the participants forget to carry out activities several times in a week, while one-third of them don‘t forget often. Among the rest of them, those who forget often daily, is less than those who forget several times in a month.
- Around half of the participants want to use reminder 30 minutes or 24 hours before their activity. While a big number, nearly half the participants prefer to use the reminder 12 hours before activity. Some of them also prefer 5 – 15 minutes duration.
- Most of the participants need reminder in the morning. One fourth of them need at the afternoon, some of them, less than one fourth, needs in the evening and at night. Few people need in the noon as well.
- Two third of the participants think the weather based reminder will assist their daily life.
- Two third of the participants want a reminder system in their living room as well as at the office. Some of them prefer to have a reminder at the kitchen, living room, washroom, gymnasium, laundry room and at the shopping mall. Very few people also referred garage, bank, club, hospital or stadium.
- Most of the participants forget to take medicine. Some other issues like feeding pets, watering plants, taking key/wallet/identity card, forwarding a letter or appointment/jogging time which the participants forget to perform in their daily life.
- Some of the participants gave their opinion as comments, for instance, they would like to have a calendar system which will assist in their daily

office activities, they would like to have reminder while applying for jobs, reminder, which will be adjusted according to the needs of the customer, or reminder which has synchronization with cloud facilities.

5.2 Interview

Interviewing is a systematic way of conversation to collect data from individuals as well as to gain knowledge [37].

There are different types of interviews, for example:

Structured Interview: Structured Interview is also known as standardized interview. The same question set is used to interview all participants.

Semi-structured Interview: It is a non-standardized interview. This type of interview is frequently used in qualitative analysis. Interviewers do not research and the questions can be reordered depending on the interview.

Unstructured Interview: It is non-directed interview. Each interview is different. In this type of interview, interviewees are encouraged to express their opinion in as much detail as possible.

Non-directive Interview: In non-directive interviews, questions are usually not pre-planned. The interviewer, most of the time listens. The interviewer leads the conversation and follows what the interviewee has to say.

In this study, we had conducted a structured interview, because we wanted to ask the same questions to all participants. We had prepared a set of questions for the participants. We sent the questionnaire to the Karlskrona Municipality and only four elderly persons from the Municipality participated in the interview.

5.2.1 Aims of interview

Through the interview that we have had with the elderly people, we tried to get information on their daily drinking activities. By doing so, it enabled us to acquire the pattern of drinking habits of the participants.

5.2.2 Interview Design

In our interview, we preferred standardized style. We designed a set of questions and sent those to all participants to answer. All questions were related to drinking habits in daily life. We asked participants what type of drink they usually consume, at around what time they feel thirsty, how much they drink each time, which hand they usually use to take a drink. Besides, what is their usual routine to wake up and sleeping?

Detailed questionnaire is presented in Appendix C.

5.2.3 Transcribing

Written answers of the interview questions are used for interviewing. The participants answered the questionnaire provided by us and returned it to them. Thus, we have collected all the information specifically. The answers of the participants are included in Appendix D.

5.2.4 Data Analysis

For analysis of interview data, we have used the qualitative data analysis (QDA) method. According to Seidel (1998) [38], ―Qualitative data analysis is best understood as a symphony based on three elegant but simple notes—noticing, collecting, and thinking".

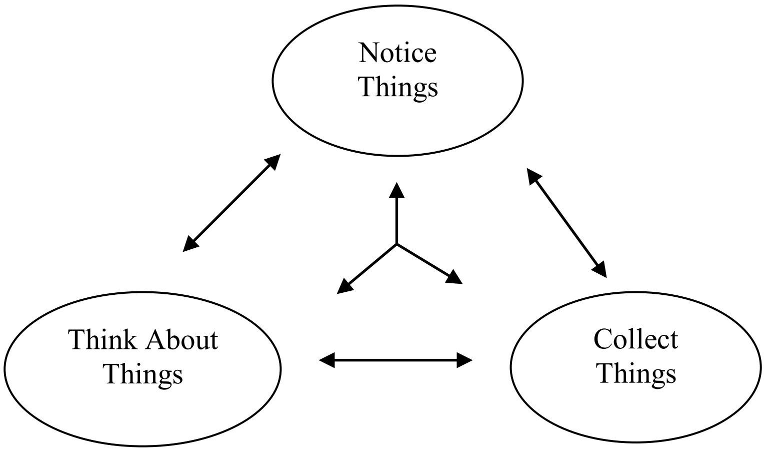

Figure 8: Quality Data Analysis Process (Seidel, 1998)

After noticing interesting things, a ‗code' can be given to those things. These codes can be used to sort and collect things. These three steps are cyclical and interlinked.

5.2.5 Interview Analysis

Here is the summary of the result from the interview:

- World population ageing is growing day by day and elderly people do not have enough caretakers to provide care for all of them.
- Most of the time elderly people are totally dependent on the care provider.
- There is no such reminder system implemented in an elderly care home, which can be used to remind different activities.
- Elderly people usually forget to take their medicine in time.
- They also forget to drink the least amount of liquid (water, juice) required for them to keep healthy.
- Most of them go to bed early around 22:00 and before 00:00. Most of them do not wake up until 7:00 am.
- Before going to bed around 22:00, they usually want to take something to drink and it is about 1 dl of liquid that they prefer to consume during that time. They usually want to drink water, milk, juice, green tea, coffee or cider. Before going to bed they usually take their drink from the kitchen.
- Water is their most common drinking item.
- They usually use their right hand to take their drink.
- During the day, participants want to consume approximately 1.2 to 2 liters of liquid.
- Different participants want to start drinking at different time after waking up. For instance, one participant chooses to drink immediately after waking up while another waits to drink until finishing breakfast. The rest of the participants opt to start drinking 1:30 to 2 hours after wake up.
- Consumption of liquid ranges from a minimum of six times a day to a maximum of ten.

According to the survey and interview analysis, we conclude that context aware reminder system could be a good solution for the users. To build such a system, user activity recognition is the most important issue to come up with this type of reminder system which can be implemented by using a Smartphone.

6 EXPERIMENT

In this section we have described the experimental approach and the outcome of the experiment for answering the research question 2. The steps are as follows:

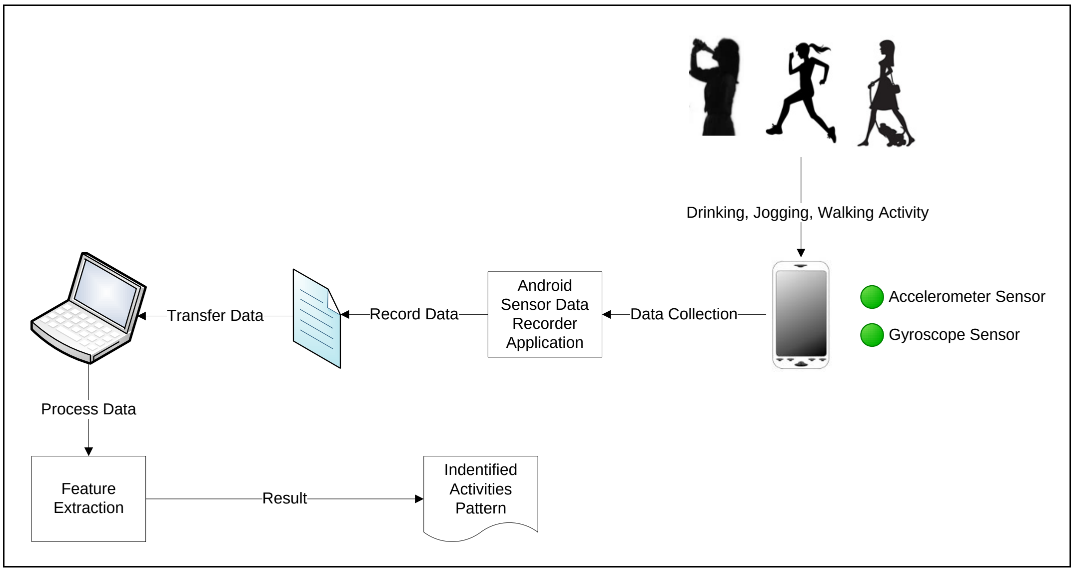

Figure 9: Experimental process

In the section 6.6, we have proposed a model to use our experimental results which is to answer the research question 2 (b).

6.1 Data Collection

In the first phase of the experiment, we collected user‘s specific activities (walking, jogging and drinking) data using Smartphone sensors, accelerometer and gyroscope. Accelerometer sensor returns the acceleration values along x, y, z axis in the units of m/s^2 and gyroscope sensor returns the rotation rate in rad/s around the device's x, y, and z axis [39]. Data acquisition rate was 100 samples per second. We invited 12 volunteers and installed our experimental data recorder application in the Smartphone and asked them to use that application during performing the selected three activities. While the volunteers were performing the activities during the experiment, the Smartphone was attached to their wrists with a wrist band.

The data collection process is described in details in the following sections:

6.1.1 Data Recording Application

We have recorded Smartphone sensors (accelerometer and gyroscope) data using our data recording application.

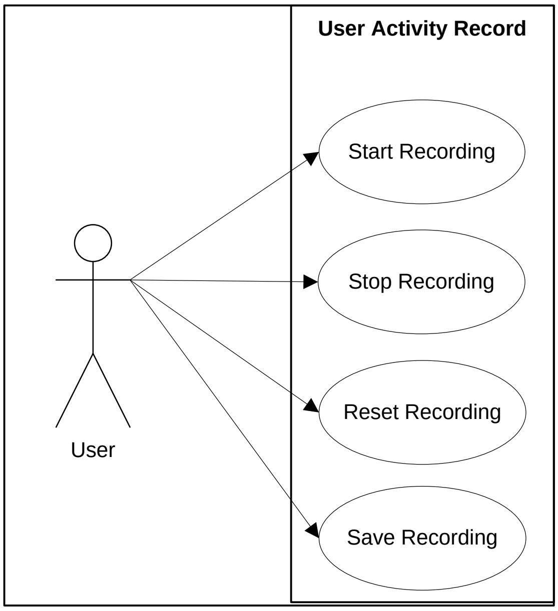

Figure 10: Use case of User Activity Recorder

We have developed an Android application to record the sensors (accelerometer and gyroscope) data. In the graphical interface of the application, there are three parts:

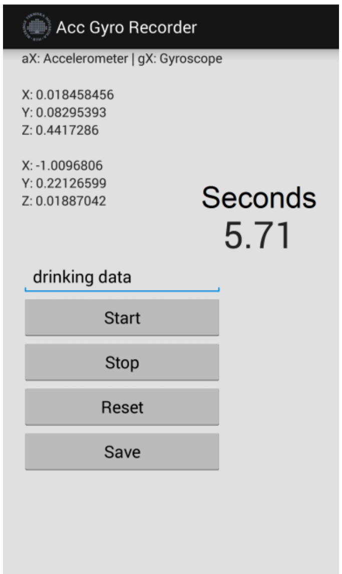

Figure 11: Interface of the Android application to record sensor data

Part 1: it shows the both sensor‘s values (x, y and z) in an interval of 0.01 seconds.

Part 2: there is an input text box to provide the file name. Using this filename, the application creates a text file (.txt format) in the ―sensordata" directory of the Smartphone‘s internal memory and writes the sensors (accelerometer and gyroscope) data in that text file.

Part 3: this application contains four buttons START, STOP, RESET and SAVE which are used to control the recording of the data. The application starts recording when START button is pressed and stop the recording when STOP button is pressed. The RESET button is used to reset the application. When SAVE button is pressed, the application completes a record and prepare for a new reading. When the application starts recording, it saves the sensors‘ data in the text file each time with the sensors new event values.

The data recorder application accesses the sensors using hardware package provided by Android SDK. In the application, *SensorManager* class object is used to access the hardware components (accelerometer and gyroscope) of the device. To listen to the new events of the sensors, we have used *SensorEventListener* interfaces provided by Android SDK. In addition to these classes, we also have implemented a *SensorData* class which deals with the sensor data to prepare them to write in a text file.

SensorManager and *SensorData* classes are explained with their implemented methods and parameters in the following sections.

6.1.1.1 SensorManager

SensorManager class allows to access the device's sensors and this class is used to create an instance of the sensor service. *SensorManager* class provides various methods for accessing and listing sensors [39].

Two methods from *SensorManager* class have been used in our application [40]:

1. **public boolean** registerListener(SensorListener listener, **int** sensors, **int** rate)

The method *registerListener* registers a sensor event listener for the given sensor. It uses listener parameter which is a SensorEventListener object. The sensor parameter is the Sensor to register to. The rate parameter is the rate sensor events are delivered at. Usually events are received faster. We have used SENSOR_DELAY_FASTEST constants which provide 100 samples per second. Our data recording application can record maximum 100 samples per second.

2. **public** Sensor getDefaultSensor(**int** type)

We have used this method to get the default sensor for a given type and we have specified the sensor type with *Sensor.TYPE_LINEAR_ACCELERATION* and *Sensor.TYPE_GYROSCOPE*. These constant values are used while differentiating the types of the sensors in the same code snippet.

6.1.1.2 File Management

Activity data was recorded in a text file. We analyzed the text file data manually. Text files are human readable. On the other hand, text file format did not affect the performance in our experiment.

A snapshot of a sample data file is shown in the Figure-12. The first row of this file is the header part. The header consists of s, xA, yA, zA, xG, yG and zG.

- s = time in milliseconds
- xA, yA, zA = x, y, z axis data of accelerometer sensor
- xG, yG, zG = x, y, z axis data of gyroscope sensor

	A	B	C	D	E	F	G
1	s	xA	yA	zA	xG	yG	zG
2	0	0.652976	0.092341	0.541879	-0.05712	-0.3204	-0.03787
3	0.01	-0.51295	-0.13296	0.154673	0.002443	0.223882	0.005498
4	0.02	-1.39051	-0.3931	-0.21466	0.006414	0.602313	-0.0055
5	0.03	-1.67319	-0.40724	-0.44692	0.007941	0.71624	-0.03207
6	0.04	-1.42657	-0.2004	-0.40354	0.020464	0.745561	-0.03421
7	0.05	-0.93809	0.013825	-0.13431	0.048869	0.5791	-0.01374

Figure 12: Data sample of drinking activity

6.1.1.3 Activity

In Android, Activity is an application component that takes care of creating a screen for the application with which users can interact in order to do something. For instance, in the application which is used in this experiment, users can type the filename, start or stop the application or see the sensor‘s data changes.

We have followed the Activity lifecycle, documented in Android developer documentation [41] to design application‘s user interface. Activity class has some important methods which we have used in our application by overriding:

- **public void** onCreate(Bundle savedInstanceState)
- **public void** onSensorChanged(SensorEvent event)

6.1.2 Data Collection Procedure

After developing the Android application, the next phase was to collect data using the application. Samsung Galaxy S4, which is operated by Android 4.3 Jelly Bean, is being used to collect experimental data.

The experimental data was collected for three types of human activities - walking, jogging and drinking. Data was recorded for 120±2 seconds for each sample and data acquisition rate was 100 samples per second.

The experimental data was collected from 12 volunteers. We invited more than 12 volunteers, but only the 12 have agreed to participate in the experiment. During the experiment each volunteers had the Smartphone placed on the wrist of the right hand by a wrist strap.

Figure 13: Smartphone placement on the right hand‘s wrist

At the beginning of data collection, it was documented experiment time and experiment type. The data was collected in different environments. For walking and jogging, data was collected outside of the home environment. Road and park have been used to collect data for walking and jogging activity. On the other hand, for drinking activity, data was collected at the home environment. Each experiment was led by one of the thesis students to guide the volunteer to ensure collecting data in the correct process.

After collecting the samples, the data was transferred to the laptop (Windows OS) via USB or Bluetooth for further analysis.

The following figure shows the graph from a recorded sample data of the accelerometer sensor and the consecutive figure is showing the graph of gyroscope sensor data:

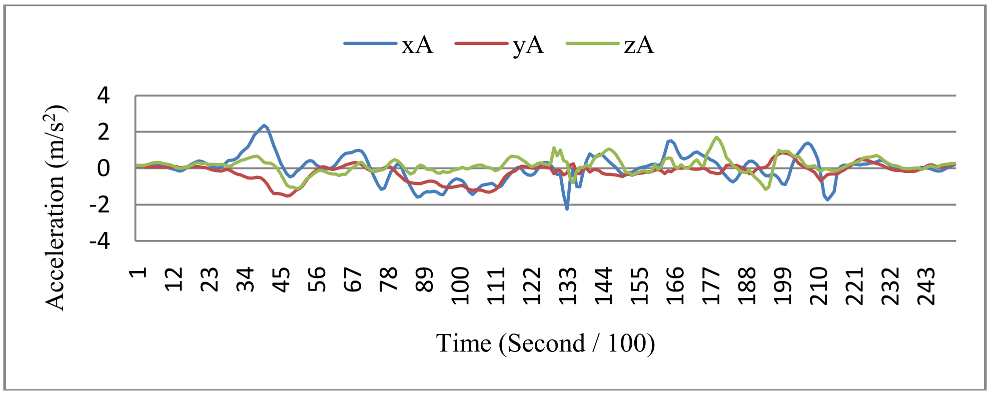

Figure 14: Accelerometer data (x, y and z) of the drinking activity

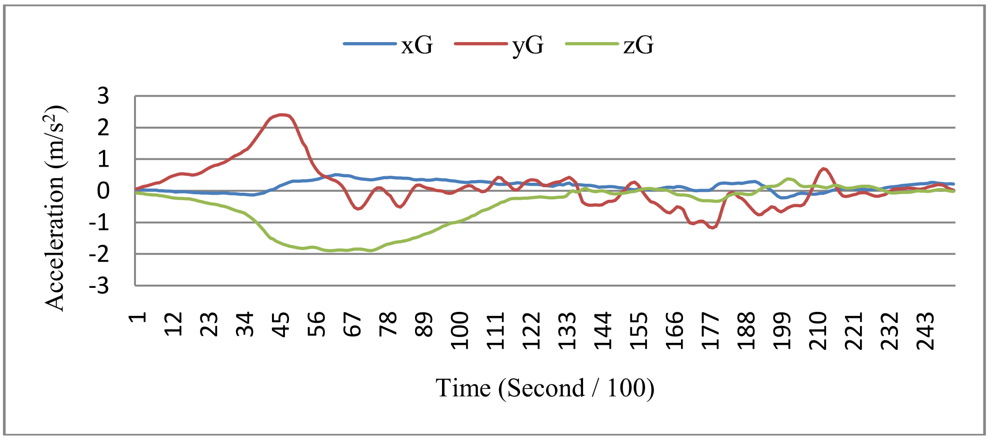

Figure 15: Gyroscope data (x, y and z) of the drinking activity

6.1.3 Pilot Test

A pilot test was conducted before final experimental data collection with the aim to test whether the developed application works in the defined test procedure and also to evaluate whether the tests seemed reasonable. During the testing, several factors were being observed to see if the data was collected at an expected rate. The created file format on the phone memory was also checked whether the file format is readable or not. Also checked if there is any of the data was missing, data overlapping, software or hardware interruptions during the recording data or any other bugs are present in the application. Then, demo data was collected in the same way the experimental data was collected and analyzed to find bugs. After fixing the pilot test, the final experimental data was collected.

6.2 Feature Extraction

We have recorded accelerometer and gyroscope sensor‘s data (x, y and z axis values) after every 0.01 seconds using a Smartphone for three different activities such as walking, jogging and drinking. The data was then extracted for further analysis.

Steps that have been followed to acquire the features is described below in brief:

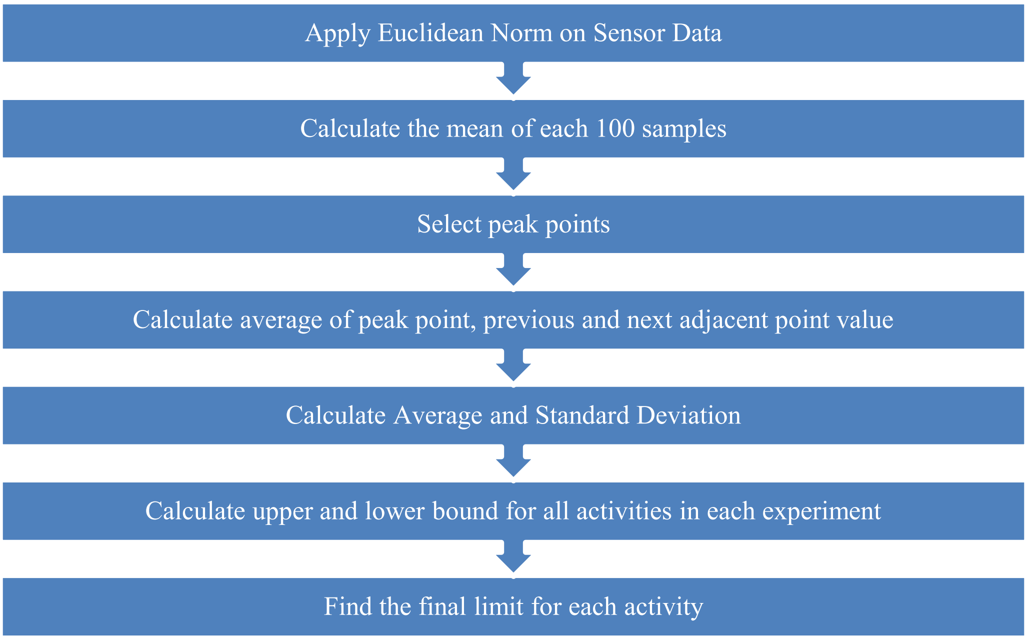

Figure 16: Calculation process

Details of the calculation process with their output are described below.

6.2.1 Calculate Mean of each 100 values

We acquired tri-axial (x, y and z) value from the accelerometer and gyroscope sensor at the rate of 100 samples per second. That means, for each second, we have 100 rows of data consisting of three values (x, y, and z axis values). We applied the Euclidean distance formula on the tri-axial accelerometer and gyroscope sensor‘s output signal data. Signal Vector Magnitude (SVM) = $\sqrt{x^2 + y^2 + z^2}$, which measure the degree of body movement as obtained from the tri-axial accelerometer [42] and tri-axial gyroscope output signal.

First of all, for each row, we squared each axis value (x^2, y^2 and z^2) and then summed up those squared values ($x^2 + y^2 + z^2$). Then, we calculated the square root of the resulting sum value ($\sqrt{x^2 + y^2 + z^2}$). Thus, for 100 rows, we got 100 squared root values. Finally, we averaged these 100 squared root values and acquired one average value for each second. Using this average value for each second in a sample data, we generated a graph to observe the pattern. The overall process is performed by using the following equation.

$$\rightarrow \mu_{\mathrm{SVM}} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{SVM}_i, \text{ where, SVM} = \sqrt{x^2 + y^2 + z^2}, \text{ and n} = 100;$$

The following figure demonstrates a sample graph of drinking activity generated using the average value for each second:

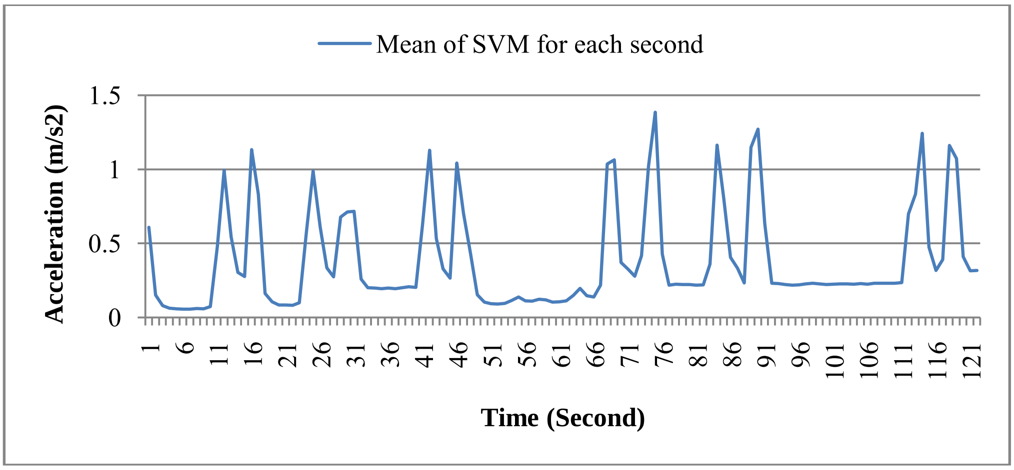

Figure 17: Time VS Mean of SVM for each second of Accelerometer for drinking activity

6.2.2 Select Peak Point

In this step, we studied the graphs which were generated by the calculated average value in the previous step (6.2.1) for different activities. In each graph, value changes in every second and we selected the peak point (PP) values for the next calculation.

After selecting the peak point (PP) value, we considered its next two points, adjacent previous point (in short APP) of PP and the adjacent next point (in short ANP) of PP. We named these three points (PP, APP and ANP) together at peak neighborhood points (PNP). Then, we calculated the average of these three values (PNP).

We considered the mean value of Peak Neighborhood Points (PNP) to get the activity pattern. Because, only the peak point value is not providing the significant pattern to identify the activity. We observed some similar activities with the drinking activity as like wearing spectacles and combing hairs activity. Often we found, those activities peak points level is similar with each other. It is not possible to distinguish the activities on the basis of only peak points. Then we observed the peak adjacent points (APP and ANP) and we found, they have the significantly different distance values with the PP. We calculated the mean of PNP (PP, APP and ANP) and obtained the meaningful pattern for each activity.

The following Figure-18 demonstrates the example of four PNP. In the first PNP, the value of the peak point (PP) is 1.148. The adjacent previous point (APP) is 0.994 and the adjacent next point (ANP) is 0.524. The calculated average of these three points is 0.8887. In this way, all the PNPs are calculated. In this example Figure-18, the four PNP values and their calculated average have been shown in the following Table-5.

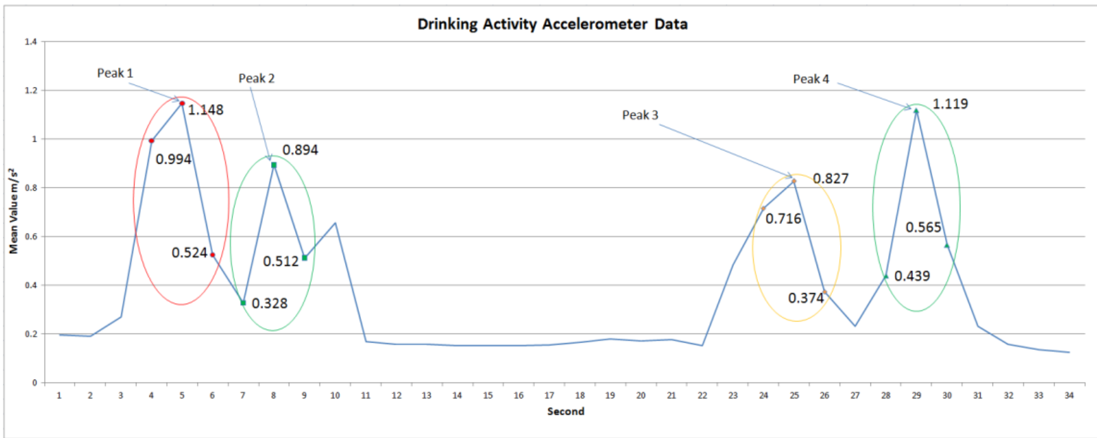

Figure 18: Example of PNP selections in a drinking sample of accelerometer

Example of Peak Neighborhood Points (PNP) calculation in a drinking sample:

	PNP 1	PNP 2	PNP 3	PNP 4
Adjacent previous point of peak point (APP)	0.994	0.328	0.716	0.439
Peak point (PP)	1.148	0.894	0.827	1.119
The adjacent next point of peak point (ANP)	0.524	0.512	0.374	0.565
Mean	**0.889**	**0.578**	**0.639**	**0.708**

Table 5: Mean values of PNP of drinking activity sample

6.2.3 Calculate Average and Standard Deviation (STD)

From the previous step, we assembled several PNP values in each sample of the activities. For a single sample, we calculated average of all PNP values in that sample and acquired an average value for that particular sample.

In the same way, we also calculated the standard deviation of all PNP values in a particular sample and got a single standard deviation value for that sample. Thus, after this step, we acquired one average value and one standard deviation value for a single sample of a particular activity (walking, jogging or drinking). Hence, for the twelve samples, we got twelve different average and standard deviation values for each activity.

The following table shows all the selected PNP values as a sample of drinking activity from the accelerometer sensor with their calculated average and standard deviation values.

Accelerometer data of Drinking activity (experiment-3)				
Peak Neighborghood points (PNP)				
PNP Samples	APP	PP	ANP	Mean of PNP
PNP 1	0.481	0.992	0.543	0.6722
PNP 2	0.276	1.132	0.832	0.7468
PNP 3	0.574	0.988	0.613	0.7249
PNP 4	0.627	1.129	0.532	0.7629
PNP 5	0.264	1.043	0.701	0.6692
PNP 6	1.035	1.063	0.370	0.8230
PNP 7	1.024	1.386	0.427	0.9455
PNP 8	0.359	1.164	0.803	0.7756
PNP 9	1.147	1.272	0.634	1.0177
PNP 10	0.833	1.243	0.474	0.8499
PNP 11	0.390	1.161	1.072	0.8745
			Average	**0.8057**
			Standard Deviation	**0.1099**

Table 6: List of PNPs, calculated Average and STD

6.2.4 Calculate upper and lower bound

In the previous step, we composed the list of average and standard deviation values consisting of 12 samples of an activity. In the current step, our target was to find a range (upper and lower bound) for that particular activity, so that these values could be used as margin to identify that activity.

To do so, we have used average and standard deviation values which we got from the previous step. In case of drinking activity, for a single sample, the upper bound was selected by adding the standard deviation to the average value of that particular sample. And the lower bound was selected by deducting the standard deviation from the average value.

Upper bound = Average + Standard Deviation
Lower bound = Average – Standard Deviation

The following table shows the calculated upper and lower bound value for the drinking activity (experiment-3) using the average and STD which we got from the previous step shown in Table-6.

Average of PNP	Standard Deviation (STD)	Upper bound Average + STD	Lower bound Average – STD
0.8057	0.1099	0.9155	0.6958

Table 7: Upper and lower bound for drinking activity

Jogging and walking activities are associated with high amplitude signal values of the accelerometer and gyroscope sensor, compared with the other activities like drinking, combing hair, wearing spectacles, washing face, etc. Their amplitude signal value difference is higher with different users. So, the jogging and walking activities need a wider range to predict jogging and walking activity more accurately, compared with other activities like drinking activity.

To calculate the upper and lower bound for the walking and jogging activities, we added and deducted twice the value of the standard deviation from the average value. Because, in the experiment, we found that the range using (STD * 2) for walking and jogging, covers most of the mean of PNP during that activity. This is providing a better prediction in identifying the activity, but yet does not overlap different activities for a particular value. This is also shown in Figure-19.

Upper bound = Average + (Standard Deviation * 2)
Lower bound = Average – (Standard Deviation * 2)

6.3 Experimental Results

We have calculated upper and lower bound for each activity (walking, jogging and drinking). All the resulting values for each experiment are documented in the following Table 8-10.

In the Table 8-10, there are nine columns. First column depicts the experimental sample number. Next four columns are for accelerometer values and the rest of the columns are for gyroscope values. In these four columns, the first column is showing the average value of all the instances of peak neighborhood points (PNP) in a sample data. In the same way, the next column STD shows the standard deviation calculation of all Mean of PNP in that particular sample data as we can in Table-6. Next two columns are calculated using the average and STD column values. *Upper* column is showing the upper bound of an activity which is calculated by adding STD value with average, on the other hand, *Lower* column, which is for the lower bound, is calculated by deducting STD from average. In the same way, the rest of the four columns show the values that have been acquired after processing the gyroscope data.

The following Table-8 is for the drinking activity. In drinking activity, average and STD values are found below 1 for both accelerometer and gyroscope. Upper bound is selected to be 1.114 in case of the accelerometer, which is the highest value in *Upper* column. On the other hand, the lower bound is selected to be 0.436 which is the lowest in *Lower* column. Following the same selection process as that of accelerometer, the lower and upper bound for gyroscope is selected 0.342 and 0.958 respectively.

Drinking Activity								
Sample	Accelerometer				Gyroscope			
	Average of PNP (APNP)	STD of PNP (SPNP)	Upper bound (APNP + SPNP)	Lower bound (APNP - SPNP)	Average of PNP (APNP)	STD of PNP (SPNP)	Upper bound (APNP + SPNP)	Lower bound (APNP - SPNP)
S1	0.9704	0.1444	***1.1148***	0.8260	0.8052	0.1533	***0.9585***	0.6519
S2	0.9574	0.1108	1.0682	0.8466	0.6372	0.1006	0.7378	0.5367
S3	0.7511	0.1324	0.8835	0.6187	0.6627	0.1853	0.8481	0.4774
S4	0.4852	0.0484	0.5337	***0.4368***	0.4452	0.1030	0.5482	***0.3422***
S5	0.6231	0.0965	0.7196	0.5266	0.4687	0.0620	0.5307	0.4067
S6	0.6748	0.1078	0.7826	0.5670	0.7052	0.0902	0.7954	0.6150
S7	0.7006	0.1021	0.8027	0.5985	0.7462	0.0721	0.8183	0.6742
S8	0.8057	0.1099	0.9155	0.6958	0.8418	0.1037	0.9455	0.7381
S9	0.6178	0.0740	0.6918	0.5439	0.6538	0.0922	0.7461	0.5616
S10	0.5589	0.0271	0.5860	0.5318	0.6238	0.0640	0.6878	0.5598
S11	0.7706	0.0369	0.8074	0.7337	0.8530	0.0823	0.9353	0.7707
S12	0.6472	0.0595	0.7067	0.5877	0.7137	0.0963	0.8101	0.6174

Table 8: Upper and lower bound list of all Drinking activity samples

The following table demonstrates the calculation for the walking activity. From the table, upper and lower bound value is selected 5.553 and 2.506 for the accelerometer. And for gyroscope, the upper bound value is 2.851 and lower bound value is 0.64

Walking Activity								
Sample	Accelerometer				Gyroscope			
	Average of PNP (APNP)	STD of PNP (SPNP)	Upper bound (APNP + SPNP*2)	Lower bound (APNP – SPNP*2)	Average of PNP (APNP)	STD of PNP (SPNP)	Upper bound (APNP + SPNP*2)	Lower bound (APNP - SPNP*2)
S1	3.3063	0.1911	3.6886	2.9241	1.1459	0.1538	1.4536	0.8382
S2	3.8816	0.1996	4.2808	3.4824	1.3137	0.2815	1.8767	0.7507
S3	3.6711	0.2297	4.1304	3.2117	1.1974	0.1614	1.5202	0.8746
S4	3.6806	0.2870	4.2545	3.1067	1.5308	0.4435	2.4178	***0.6439***
S5	3.5086	0.5009	4.5104	***2.5069***	1.2676	0.2734	1.8144	0.7207
S6	3.8441	0.6192	5.0825	2.6056	1.2604	0.1928	1.6460	0.8748
S7	3.4283	0.2271	3.8826	2.9741	1.1139	0.1982	1.5104	0.7174
S8	3.9217	0.4984	4.9185	2.9249	1.4954	0.3466	2.1886	0.8023
S9	3.6945	0.4377	4.5699	2.8191	1.6097	0.1956	2.0010	1.2184
S10	4.0075	0.3394	4.6863	3.3286	2.2164	0.2364	2.6891	1.7437
S11	4.4212	0.5664	***5.5539***	3.2884	2.2626	0.2944	***2.8513***	1.6739
S12	3.6818	0.4913	4.6643	2.6992	1.6107	0.1875	1.9856	1.2357

Table 9: Upper and lower bound list of all Walking activities samples

In the following table, jogging activity values are demonstrated. Upper and lower bound values of jogging activity of accelerometer sensor are 15.996 and 9.576. For gyroscope, the upper bound is 4.566 and the lower bound is 1.797.

Jogging Activity								
Sample	Accelerometer				Gyroscope			
	Average of PNP (APNP)	STD of PNP (SPNP)	Upper bound (APNP + SPNP*2)	Lower bound (APNP – SPNP*2)	Average of PNP (APNP)	STD of PNP (SPNP)	Upper bound (APNP + SPNP*2)	Lower bound (APNP - SPNP*2)
S1	13.3555	0.9805	15.3166	11.3945	3.0701	0.2773	3.6248	2.5154
S2	13.1851	1.1664	15.5180	10.8522	2.9657	0.3070	3.5797	2.3516
S3	12.8977	1.4225	15.7427	10.0526	2.6688	0.4358	3.5405	***1.7971***
S4	14.2590	0.7432	15.7454	12.7726	3.0307	0.1923	3.4153	2.6460
S5	13.8866	0.9389	15.7644	12.0087	3.7718	0.2911	4.3540	3.1897
S6	13.6659	1.1652	***15.9963***	11.3356	3.8180	0.3633	4.5446	3.0914
S7	12.9333	1.0804	15.0942	10.7725	3.6796	0.1991	4.0779	3.2814
S8	12.5652	0.8387	14.2426	10.8879	3.5919	0.2867	4.1653	3.0186
S9	11.8497	1.1365	14.1226	***9.5767***	3.5668	0.4997	***4.5663***	2.5674
S10	12.2992	0.6271	13.5535	11.0450	3.3478	0.3646	4.0769	2.6186
S11	11.9446	0.8507	13.6459	10.2433	3.2489	0.2833	3.8156	2.6823
S12	12.4657	0.4343	13.3342	11.5971	3.4503	0.3259	4.1022	2.7985

Table 10: Upper and lower bound list of all Jogging activity samples

6.4 Validation

We have used machine learning tool WEKA to evaluate our approach. Machine learning and data mining approaches are used to classify the information. Machine learning is the study in the field of the computer science which concerns with the construction of an algorithm that is able to classify the information it hasn‘t seen before, by learning the patterns from the training data [12]. For example, a machine learning algorithm could be trained on email messages to learn to distinguish between spam and non-spam messages, and then it can be used to classify new email messages into spam and non-spam directories. Data mining is about solving the problems by analyzing the data already present in the database [12]. This is defined as the procedure of detecting patterns in the data. The procedure must be automatic or semiautomatic and the discovered patterns must be significant in a way that they lead to some advantage.

To evaluate our activity recognition method, we prepared the evaluation dataset with the processed data which is acquired from the three different activities: walking, jogging and drinking. In our experiment validation process, we used a classifier algorithm to classify those processed data for each activity.

6.4.1 Dataset Preparation to Evaluate

Experiment samples were total 36 for three different activities. We collected randomly mean of each PNP value (an example is shown in Table-6) of accelerometer and corresponding gyroscope data from all 12 samples for each activity. From the 12 samples for each activity we collected 92 instances. From each sample, we collected 8±2 instances, where each instance is formed with three values:

- Mean of each PNP of accelerometer data
- Mean of each PNP of gyroscope data
- Activity name (Drinking, Walking, Jogging)

We prepared the dataset in the ARFF file format which contains of 276 instances, two numeric attributes (accelerometer and gyroscope) and three classes (Jogging, Walking and Drinking). An example of the dataset is shown in APPENDIX-F, Figure-40.

In this experiment J48 algorithm was used to analyze the activity data. J48 is a tree based learning approach. This algorithm is developed by Ross Quinlan. J48 is the Java implementation of C4.5 algorithm [11]. C4.5 algorithm is an extended version of ID3 algorithm. This algorithm uses divide-and-conquer approach to split a root node into a subset of two partitions till leaf node occurs in the tree. Some of the following attributes of the J48 algorithm motivated us to select this algorithm. It can handle missing data and numeric attributes. It performs pruning to increase accuracy and decrease tree size. J48 includes minor bug fixes from C4.5 algorithm. This algorithm is one of the most popular algorithms.

We used J48 algorithm with cross-validation to evaluate the accuracy. There exist several kinds of cross-validation approaches.

In one round of cross-validation, the sample dataset splits into complementary subsets. Then, it performs the analysis on one training set and validates the analysis on the testing set. Multi rounds of cross-validation are used to reduce the inconsistency of the accuracy. In this cross-validation, dataset splits into in multiple partitions and the results are averaged over the rounds. The 10-fold cross-validation is commonly used in multi rounds of cross-validation. In 10-fold cross-validation, data splits into 10 sets of size n/10. Then, it performs training process on 9 datasets and test on 1 dataset. It repeats the process 10 times and takes an averaged accuracy. In the evaluation, 10-fold cross-validation approach was applied and the acquired results are as follows:

Data Classes	Correctly Classified Instances	Incorrectly Classified Instances	Total Instances
Jogging	92	0	92
Walking	91	1	92
Drinking	91	1	92
Total	274	2	276
Correctly Classified Instances about: 99%			

Table 11: The accuracy result for three activities using J48 classifiers in WEKA tool

According to the confusion matrix (shown in Table-11), Jogging class is correctly classified with all 92 instances. Walking and jogging both classes are correctly classified with 91 instances and only 1 instance is incorrectly classified. The overall accuracy is about 99%.

According to the state-of-art, simple activities (sitting, standing, walking, running, lying, biking, etc.) were recognized with the accuracy 93% using a Multi-layer Perceptron algorithm [11]. We acquired the accuracy about 99% correctly classified instances for the three activities (walking, jogging, drinking activity) using WEKA J48 algorithm.

6.5 Experiment Results

The aim of the experiment was to recognize different human activities mainly walking, jogging and drinking using Smartphone sensors; accelerometer and gyroscope. We developed an android based application to record user activity data for our experiment. Firstly, the sensor data was collected for each activity and then analyzed to find the patterns for different activities. 12 volunteers were invited to participate for experimental data collection. The volunteers used Smartphone, equipped with the required sensors during the experiment.

After collecting sensor‘s data, we processed those data using mathematical calculations and then we generated graphs to identify the patterns in a data. After analyzing the graphs, we came up with a range of values consisting of an upper bound and lower bound value of each activity. Twelve experimental data was selected to acquire the ranges. For each experiment, one range of upper and lower bound was found. Finally, we selected the final range of an activity between lowest from the lower bounds and highest from the upper bounds of all 12 experiments of that activity. For walking, the range is found for accelerometer sensor, 2.506 to 5.553; whereas the range is 0.643 to 2.851 for the gyroscope. In case of jogging, the accelerometer data range is 9.576 to 15.996 and for gyroscope from 1.797 to 4.566. Drinking range is 0.436 to 1.114 for accelerometer data and 0.342 to 0.958 for gyroscope data.

Sensor	Walking		Jogging		Drinking	
	Lower	Upper	Lower	Upper	Lower	Upper
Accelerometer	2.5069	5.5539	9.5767	15.9963	0.4368	1.1148
Gyroscope	0.6439	2.8513	1.7971	4.5663	0.3422	0.9585

Table 12: Accelerometer and Gyroscope calculated data range of three activities

The mean of a PNP data sample of accelerometer data for three different activities (walking, jogging and drinking) have been plotted on a graph. Different activity range is marked according to the information acquired from Table 12. The amplitude range for each activity is marked and can be seen in Figure-19.

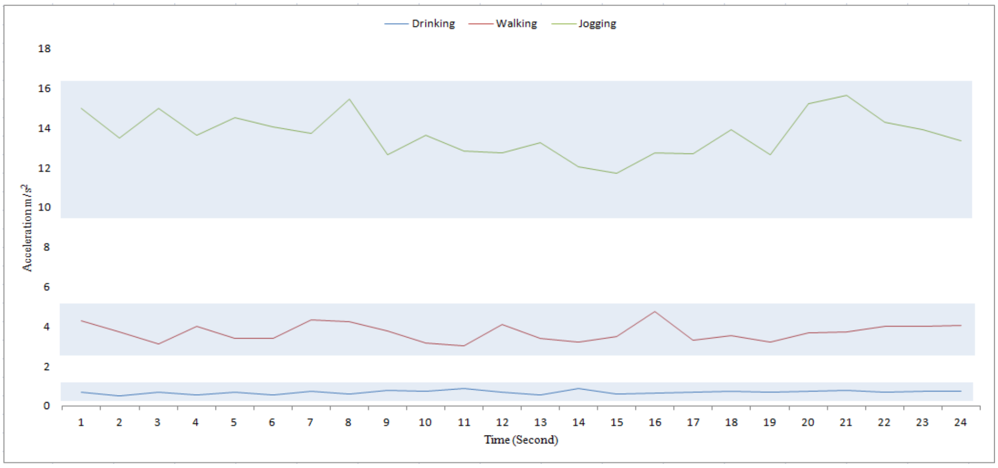

Figure 19: Jogging, Walking and Drinking activity graph (accelerometer)

After getting the different ranges of different activities; a prototype of a Smartphone application has been implemented, where the data range was used to identify the activity.

We evaluated our approach which acquired about 99% accuracy for all three activities (walking, jogging, drinking) altogether.

6.6 Activity Recognition Model

In this section we have proposed the activity recognition model which can recognize the users' specific activities (Jogging, walking and drinking) by using our experimental results:

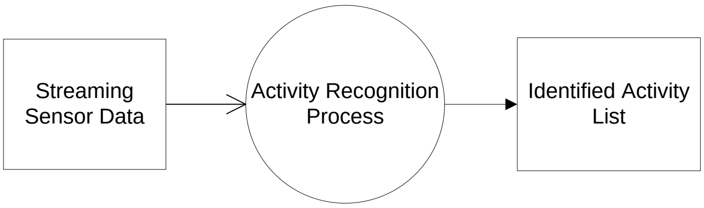

Figure 20: Activity Recognition Model

Steps of the Activity Recognition Process:

1. Get input data from the Smartphone sensors
   a. Get 3D accelerometer data in m/s^2
   b. Get 3D gyroscope data in rad/s
2. Calculate the mean value of both sensors' data according to $\mu_{\text{SVM}} = \frac{1}{n}\sum_{i=1}^{n} \text{SVM}_i$, where, SVM = $\sqrt{x^2 + y^2 + z^2}$, n = Data Frequency per second
3. Calculate the average of each peak neighborhood (2 adjacent points with peak point).
   a. Find the peak point (PP)
   b. Find the adjacent previous point (APP) of the peak point
   c. Find the adjacent next point (ANP) of the peak point
   d. Compute their (PP, APP and ANP) average
4. Continue step 3 till end of the data series
5. Compare the resultant values to the activity range

7 PROTOTYPE IMPLEMENTATION

In this section we have discussed about the prototype design and its implementation for answering the research question 3.

7.1 Prototype Architecture Diagram

The architecture diagram demonstrates how the activity recognition model can be used in a reminder system to identify any of the three activities and generate reminder based on the identified activity.

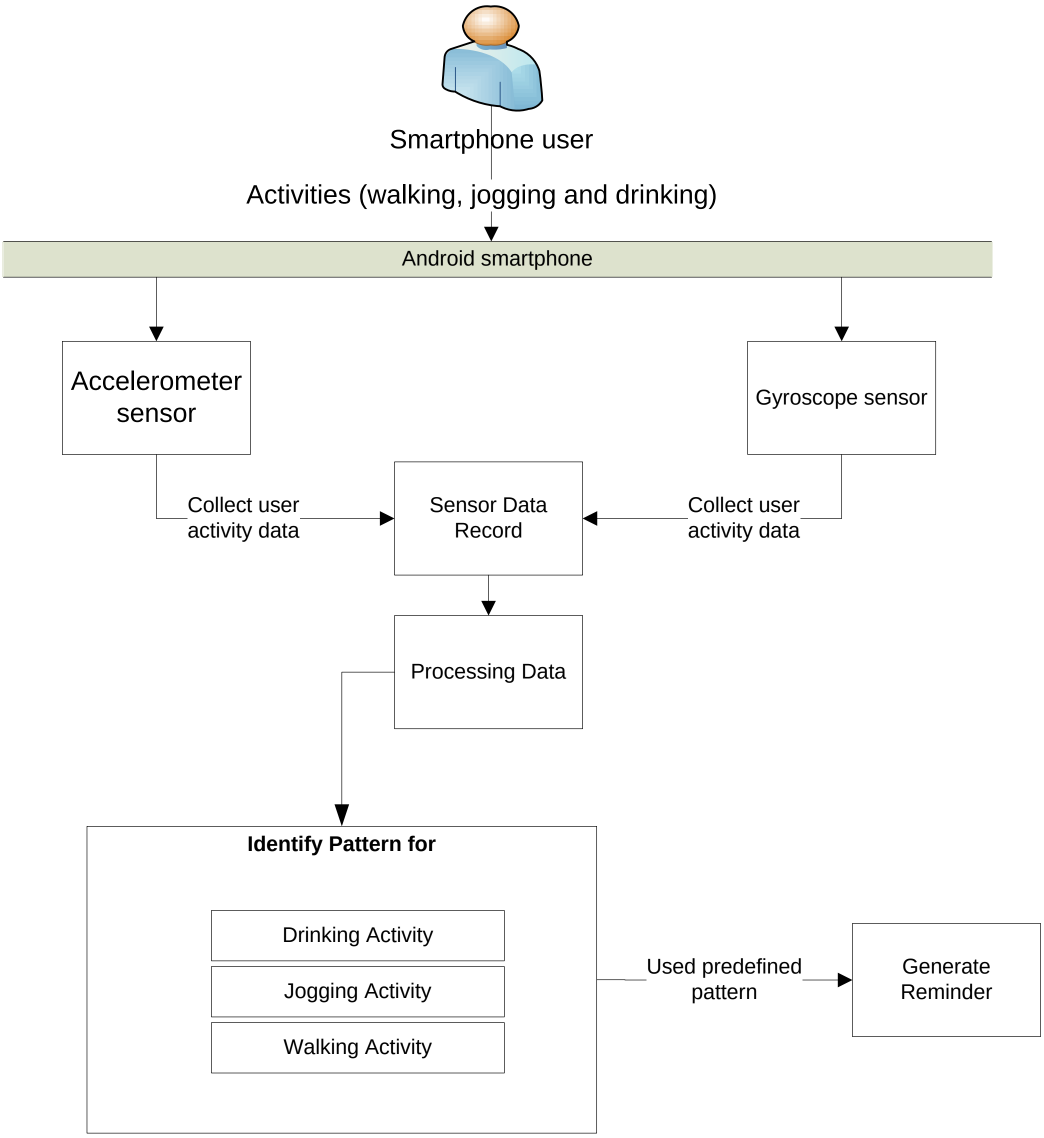

Figure 21: Prototype Architecture Diagram

The system records Smartphone's accelerometer and gyroscope tri-axial sensors' data. Then those data are processed according to the activity recognition model. Using this model, the system determines the activity which has been performed and based on this recognized activity; it generates a reminder if necessary.

7.2 Application flow chart

The following chart shows the workflow of our prototype. When the application starts, it records tri-axial accelerometer and gyroscope sensors' data and stores the data for each 30 seconds in the array. Then the activity recognition model is applied to the recorded data to identify the activity which is performed earlier. The system records identified activity to generate a reminder afterward if it is required.

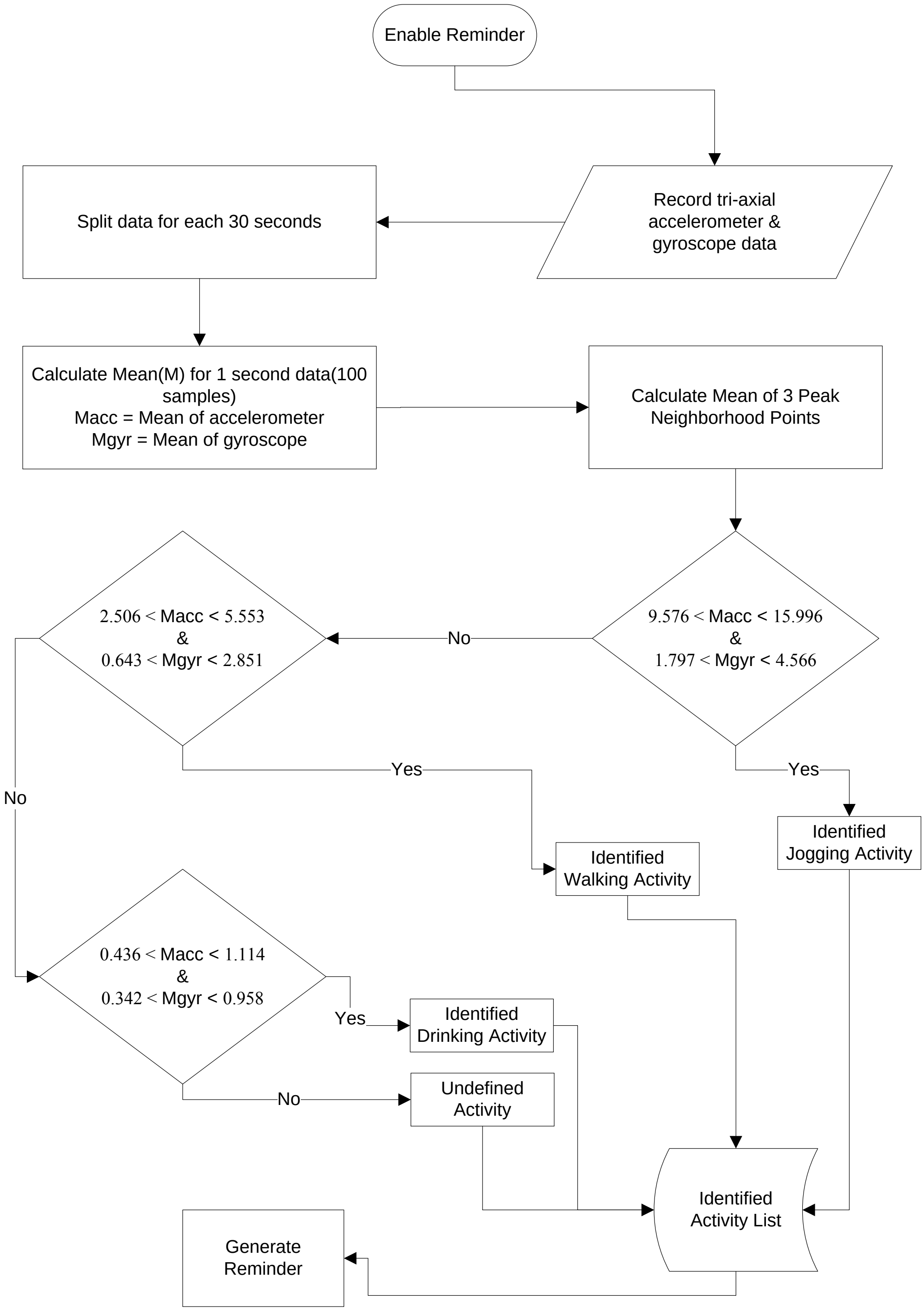

Figure 22: Flowchart of the application

7.3 Application source code

The Java implemented code is given below:

Every 0.01 second we record data in a string format like *"time, accDataX, accDataY, accDataZ, gyroDataX, gyroDataY, gyroDataZ"*. After recording the data as much as required, we parse and calculate them according to the equation to get the mean value for each 0.01 seconds.

```java
for(int i = 0; i < sensorData.size(); i=i+7) {

    try {
        //data for accelerometer sensors
        double s =  Double.parseDouble(sensorData.get(i).trim());
        double Ax = Double.parseDouble(sensorData.get(i+1).trim());
        double Ay = Double.parseDouble(sensorData.get(i+2).trim());
        double Az = Double.parseDouble(sensorData.get(i+3).trim());

        //data for gyroscope sensors
        double Gx = Double.parseDouble(sensorData.get(i+4).trim());
        double Gy = Double.parseDouble(sensorData.get(i+5).trim());
        double Gz = Double.parseDouble(sensorData.get(i+6).trim());

        accMean = Math.sqrt(Math.pow(Ax, 2) + Math.pow(Ay, 2) + Math.pow(Az, 2));
        gyroMean = Math.sqrt(Math.pow(Gx, 2) + Math.pow(Gy, 2) + Math.pow(Gz, 2));

        accMeanArrayList.add(s + "");
        accMeanArrayList.add(accMean + "");

        gyroMeanArrayList.add(s + "");
        gyroMeanArrayList.add(gyroMean + "");
    }
    catch(NumberFormatException nfe) {
        nfe.getMessage();
    }
    catch(IndexOutOfBoundsException iobe) {
        iobe.getMessage();
    }
}
```

Figure 23: Data parsing

After getting the all the mean values for each 0.01 seconds, we calculated the average values for each 1 second as we can see in the following code:

```java
private double[] getAverageMean(ArrayList<String> meanArray) {

    int count = 0;
    double uAcc =0;

    ArrayList<Double> meanUAcc = new ArrayList<Double>();
    double[] meanList = new double [2];

    for(int i=1; i < meanArray.size(); i+=2) {
        uAcc += Double.parseDouble(meanArray.get(i));
        count++;

        if(i-1 > 0 && Double.parseDouble(meanArray.get(i-1)) ==
            Math.ceil(Double.parseDouble(meanArray.get(i-1)))) {

            uAcc = uAcc/count;
            meanUAcc.add(uAcc);

            count = 0;
            uAcc =0;
        }
    }

    Double avgMeanUAcc = 0.0;
    for(int m=0; m < meanUAcc.size(); m++) {
        avgMeanUAcc += meanUAcc.get(m);
    }

    avgMeanUAcc = avgMeanUAcc/meanUAcc.size();
    meanList[0] = avgMeanUAcc;

    return meanList;
}
```

Figure 24: Method for calculating the average

After acquiring all of the calculated average of mean values for each 1 second, we calculated the average of Peak Neighborhood Points (PNP), shown in the following code:

```java
private static ArrayList<String> peakNeighbourHoodCalculation(ArrayList<String> accOrGyro) {

    ArrayList<String> resultArray = new ArrayList<String>();

    for(int i=1; i<accOrGyro.size()-4; i+=2) {
        double frstValue;
        double peakValue;
        double lastValue;
        double mean = 0;

        frstValue = Double.parseDouble(accOrGyro.get(i));
        peakValue = Double.parseDouble(accOrGyro.get(i+2));
        lastValue = Double.parseDouble(accOrGyro.get(i+4));

        if(frstValue < peakValue && peakValue > lastValue) {
            mean = (frstValue + peakValue + lastValue)/3;
            resultArray.add(accOrGyro.get(i-1)); //Time in Second
            resultArray.add(mean+""); //calculated mean of peak neighborhood points value
        }
    }
    return resultArray;
}
```

Figure 25: Calculating the average of Peak Neighborhood Points (PNP)

7.4 Prototype Interface

In the demo reminder application, a reminder can be generated based on the user's three activities (walking, jogging and drinking). The reminder application keeps the record of the user's activities. If the user forgets to perform an activity at a pre-scheduled time, the reminder prompts a message to the user.

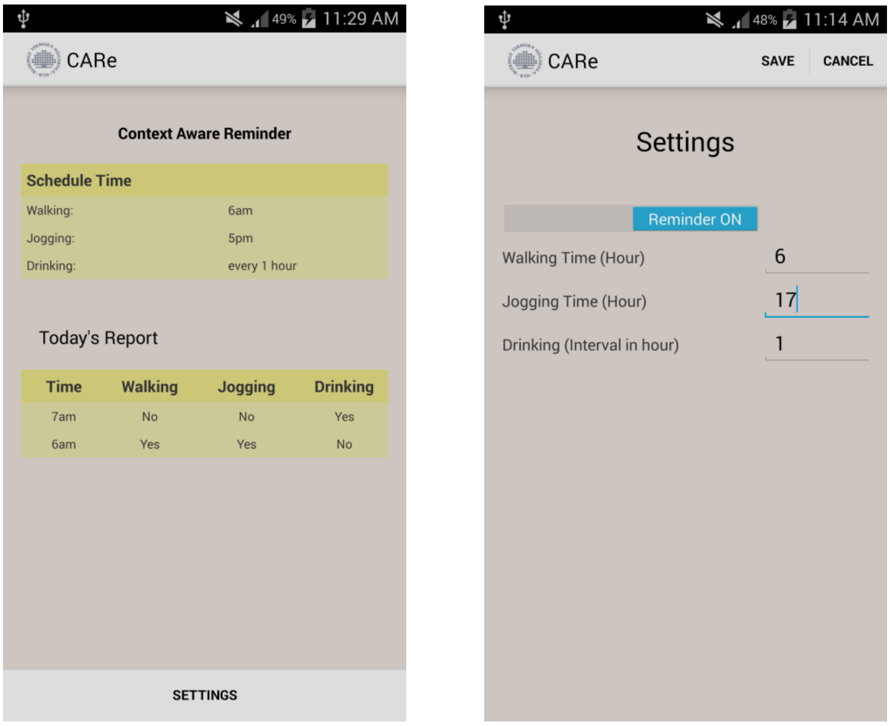

Figure 26: Demo interface of the Context Aware Reminder System

The demo reminder application contains two interfaces. First one is the main screen which is divided into two sections. Using this interface, users can check their scheduled time for three different activities and also check their performed or pending activity report in an hourly basis.

The second interface is the settings screen; using this interface a user can schedule his/her different activities.

8 DISCUSSION

We conducted surveys and interview to understand the needs of a reminder system in daily life and to identify the activities which are often and more likely to be forgotten. According to the interview, we have understood the needs of a context based reminder system in the daily life of the participants. This reminder system can produce a reminder on the basis of user activity is performed earlier. For instance, if someone is not drinking water for a long time, or forgets to take medicine, they should get a reminder.

In the experimental part, we have processed and analyzed user‘s different activities (walking, jogging and drinking) data which were recorded from Smartphone sensors (accelerometer and gyroscope) to identify the pattern for each activity, which leads us to develop a context based reminder system. This system could assist users in their daily life. If we consider only accelerometer sensor data, the activity data ranges for three different activities (walking, jogging and drinking) are perfectly separated from each other as we can see in Table-12. By using the accelerometer sensor data range it could be possible to distinguish these three activities (walking, jogging and drinking). The gyroscope data range information is not necessary in this situation. But it can be of good support while distinguishing between similar and complex activities like wearing spectacles and setting hairs.

We acquired the results with an accuracy of around 99% correctly classified instances for walking, jogging and drinking activities altogether. Our proposed model could be a support for others to develop activity recognition based application.

8.1 Validity Threats

Validity assessment is an important aspect and it should be considered at the beginning of the research. This study considered four types of validity threats, i.e. internal validity, external validity, conclusion validity and construct validity [43].

8.1.1 Internal Validity

The questionnaire of a survey can impact the quality of the survey and the response rate obtained in the survey. During the designing a questionnaire, some issues should be considered like the objectives of the survey, the targeted output, and then formulating a list of questions to obtain this required information properly. Careful considerations are needed, for example – the types of questions, words used in questions, the structure, the design and testing the questionnaire to get quality data [44].

To ensure these issues, we have discussed with our thesis supervisor and tried to find errors and missing information in the questionnaire. Then we made a test questionnaire and test survey to find and remove errors. Moreover, selecting suitable language is another challenge. For some participants, who may not understand the English very well; we translated the questionnaire in Swedish for them.

During the experiment and data analysis, several factors were being observed. Recorded data was checked whether it was recorded at an expected rate or not. Missing data and data overlapping was also checked in the recorded data. All axis values of the sensors (accelerometer and gyroscope) were considered during the calculation.

8.1.2 External Validity

Our approach can be used to recognize other activities as well, like combing hair, brushing teeth, washing face, etc. Acquired identified activity ranges for three different activities (walking, jogging and drinking) from the experiment, may not be applicable for all. But the same procedure can be used in individual calibration process.

This study considered three different activities, walking, jogging and drinking which can be classified by using only the accelerometer sensor. Gyroscope sensor is not required to distinguish these three activities. But gyroscope could be a good choice along with accelerometer sensor to recognize some other complex human activities, like combing hair, face washing, wearing spectacles etc.

8.1.3 Construct validity

Construct validity is concerned with the relationship between the design and the results that are concluded at the end of the research study. Proper planning was done to reduce construct validity threat before conducting the research study as mentioned in chapter 4.

8.1.4 Conclusion Validity

To reduce conclusion validity threat, the experiments results were critically reviewed before coming to the conclusion. The results were also verified using prototype applications as an outcome of this research study.

9 CONCLUSIONS AND FUTURE WORK

In this last chapter, we have concluded our research work. We also mentioned some further work that can be done to continue this research study.

9.1 RQ1: Which situations can be supported by reminder systems?

We conducted our surveys with 29 participants to learn how the reminder systems impacted on their daily life and how the reminder systems can be enhanced to meet their various needs. We also interviewed 4 elderly people to know about their normal drinking habits in daily life.

From the survey, it was found that most of the participants are using a Smartphone and the majority is used to using some sort of reminder system. Some of them mentioned, they usually forget to take medicine at the right time. Some of them also forget taking key/wallet/identity card, feeding pets, watering plants, forwarding a letter or appointment/jogging time, etc. Few of them are also interested in having weather based reminder system which will assist them in their daily life.

From the interview we have learned different drinking habits of the participants. They consumed different amount of liquid in a day, ranging from 1.2 to 2 liters. The participants mainly drink water, but are also used to having milk, coffee and green tea. We also found that the participants drink using their right hand. Observation of the survey and interview results helped us to choose an appropriate device and set up the experimental procedure and also taught us about some situations where context aware reminder system can be a support.

For example, if someone forgot to drink water or any kind of liquid in a certain time interval, the system could remind the user to drink. If the user forgot to take medicine on time, the system could also remind the user about it by checking if the user drank anything at the specific time when the medication was due. If the user leaves the home, this system could generate a reminder to check whether the user forgot anything necessary, such as: wallet, keys, cards, etc.

9.2 RQ2: a) How can we measure activities (walking, jogging and drinking) with technology (Smartphone accelerometer and gyroscope)? b) How can we use the measurement results to automate reminder to the users?

We collected three different user activities (walking, jogging and drinking) data using Smartphone sensors (accelerometer and gyroscope) to identify the activity patterns. We have identified the calculated data range for each activity which is stated in Table-12. According to our approach, the activity recognition process will compare the calculated value (mean of the PNP) of recorded Smartphone sensors‘ data and find a match with the activity data ranges that are available in Table-12. The matched range will be associated with one of the three activities. Based on the identified activity, reminder system can suggest user, what the user should perform next.

After the experimental process and data analysis, we came up with a model which can identify user activities (walking, jogging and drinking activity) by using the activity data ranges, which are acquired from the experimental process. Using this model reminder system can be extended to many other functionalities, such as to remind users if they forgot to take their medicine, to remind users if they forgot to attend their meeting, etc. This system also can store statistical information for further uses.

9.3 RQ3: How can we design reminders using Smartphone to be a support for the users?

We developed the prototype which generates a reminder after a certain period based on the activity that the user performed earlier. For example, individual user drinks water with two hours interval. If the reminder system detects the user didn‘t drink within the next two hours, it will remind the user to drink. Similarly, reminder system could generate a reminder based on the walking and jogging activity of the user.

9.4 Lesson Learned

There are some lessons we learned during our research work:

- Human activity patterns differ from one another. Also sensor sensitivity could be different. So the calibration process could be a better solution for individual activity recognition.
- Each axis data of both sensors (accelerometer and gyroscope) can be used separately to make the decision in the activity recognition process to reduce the prediction error rate.
- Some activities (walking, jogging, etc.) can be recognized using only accelerometer sensor, a gyroscope sensor is not required. But for complex activities, for instance, drinking, wearing spectacles, setting hair, washing faces, etc., it is hard to recognize using only accelerometer sensor. Some other sensors are also needed along with accelerometer sensor for these activities recognitions, for example gyroscope sensor.
- From the survey we have learned that some participants forget to take their keys, cards, wallet, etc. when they leave home. If it is possible to recognize whether these objects were in fact taken by the user or not, along with the user‘s activity recognition process, then the reminder system could generate a reminder if the user forgets anything based on these two identification approaches. RFID (Radio-frequency identification) tag can be useful in this context to recognize these objects, either the user took it or not.

9.5 Future Work

The efficiency of our approach can be improved by further investigation on different environment, using more sensors and devices. We have performed our experiment by attaching the device to the wrist; the same approach can be practiced by equipping the device on other parts of the body like the hip or the arm individually or simultaneously.

To increase the accuracy of the activity detection model, calibration process could be implemented. In the calibration process, the Smartphone will record the user specific activity data for a certain period. Recorded data will be examined to identify the activity detection parameters according to the experimental process which is explained in this study.

We have used two Smartphone sensors; these are accelerometer and gyroscope to identify the activities. Recently, other sensors like pressure, temperature and humidity sensors are widely available in a Smartphone, which also could be used to improve the accuracy of the activity recognition. Moreover, indoor positioning could help to take the decision of performing an activity more accurately. Connecting activity recognition with detecting the users‘ indoor position could be another significant research work. We also suggest to examine the same approach in future on different other activities like sitting down, cycling, standing up, brushing teeth or taking medicine.

Users‘ position can be identified by GPS to customize the reminder system according to local weather or altitude information. For example, if the device recognizes that the user is cycling, it can remind the user of any high altitude ahead of the rider's probable route. Or, local weather information can be utilized to suggest or remind about suitable outfits.

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APPENDIX A: SURVEY QUESTIONNAIRES

Blekinge Tekniska Högskolan (BTH)

Karlskrona, Sweden

Survey questionnaire on Reminder System

Surveyor Age (range):

☐ **20-30** ☐ **31-40** ☐ **41-50** ☐ **51-60** ☐ **61-70** ☐ **71-80**

1. Do you use any reminder system?
Yes ☐ No ☐ If yes, how often ___________________________________

2. Do you need any smart reminder system? Yes ☐ No ☐

3. Do you have a Smartphone? Yes ☐ No ☐

4. Do you use calendar system? Yes (paper based) ☐ Yes (in smartphone) ☐ Do not use ☐

5. Do you forget items to carry out?
Daily ☐ Several times in a week ☐ Several times in a month ☐ Don't forget ☐

6. Do you forget how to carry out an activity?
Daily ☐ Several times in a week ☐ Several times in a month ☐ Don't forget ☐

7. Do you have difficulties in daily activities?
Daily ☐ Several times in a week ☐ Several times in a month ☐ Don't forget ☐

8. How often do you forget to perform important activities?
Daily ☐ Several times in a week ☐ Several times in a month ☐ Don't forget ☐

9. Do you think reminder system could assist to take proper care of your kids?
Yes, sometimes I do feel ☐ No, I don't think so ☐ I don't have any kids ☐

10. Where geographically, do you want to have reminders?
Indoor ☐ Outdoor ☐ Others___________________________________

11. How long time does it take to plan the activity?
Once ☐ Until I start task ☐ Until I complete task ☐ Others____________________

12. When in time do you want to have reminders?
In the morning ☐ Noon ☐ Evening ☐ Night ☐ Others ____________________

13. Do you think reminder based on weather can assist in your daily life activities?
No ☐ Yes, daily ☐ Yes, occasionally ☐ Others______________________

Activities you may forget to perform in daily life: [please put (✓)]

	Name of activities	Yes	Notes
1	Taking Medicine	☐	
2	Feeding pet	☐	
3	Watering plants	☐	
4	Taking key, wallet	☐	
5	Taking Identity card	☐	
6	Forwarding letters, papers	☐	
7	Pay bills	☐	
8	Appointment Time	☐	
9	Jogging Time	☐	
10	Any other activities you may forget to perform in daily life		: ______________________________ ______________________________ ______________________________

Thank you very much for your co-operation.

Figure 27: Survey questionnaire

APPENDIX B: SURVEY RESULTS

1. Do you use any reminder system?	Yes – 21 No – 8
2. Do you need any smart reminder system?	Yes – 22 No – 7
3. Do you use smartphone?	Yes – 26 No - 3
4. Do you use any calendar system?	Yes (in smartphone) – 18 Yes (paper based) – 4 No, I don't use any – 4 In Computer – 1
5. Do you forget activities to carry out?	Daily - 4 Several times in a week - 9 Several times in a month - 6 No, I don't often forget – 9
6. Do you have difficulties to perform daily activities?	Daily - 3 Several times in a week - 9 Several times in a month - 5 Mostly, I don't feel any difficulties – 11
7. How long time does it take to plan the activity?	Until I complete the task – 10 Until I start the task – 10 Once – 8
8. How long before your activity you want the reminder?	24 Hours - 12 12 Hours – 8 30 mins – 14 15 mins - 2 10 mins - 3 5 mins – 2
9. When in time do you want to have reminders?	Morning – 22 Noon - 2 Afternoon – 7 Evening – 4 Night – 4 Almost all day – 1 It depends – 1
10. Do you think reminder based on weather can assist in your daily life activities?	Yes – 21 No – 8
11. Where geographically, do you want to have reminders?	Living room – 21 Kitchen – 8 Washroom – 5 Laundry room - 3 Drawing room – 6 Office – 19 Gymnasium – 4 Garage – 1 Restaurant – 7 Shopping mall – 3 Bank – 2 Club – 1 Hospital – 1 Stadium – 1 During business/study trip - 1

12. Activities you may forget to perform in daily life -	Taking Medicine Feeding pet Watering plants Taking key, wallet Taking Identity card Forwarding letters, papers Pay bills Appointment Time Jogging Time Any other activities you may forget to perform in daily life
Any other comments or suggestions?	1. I am happy with the reminder of my phone :) 2. "There is a lot of reminder system in the market. I use google calender most of the time. The smart phone reminder system is also pretty cool. Thinking of new reminder system?? It needs to be dam cool :) I like the idea of incorporating weather in the remainder is good. 3. Where I can plan my tasks for the entire month. 4. A synchronized system, with cloud facility would be a great option for me. 5. I want to reminder system that will assist my daily office activities. 6. There is a need to have a reminder system which can be adjustable according to the needs of the customer... 7. I need a reminder system which helps me to apply jobs

APPENDIX C: INTERVIEW QUESTIONS

Questions that will be used to understand how you drink and motivational factors to drink moderate.

Age:
Gender:

1. When do you become thirsty?
2. What motivates you to drink?
3. How much do you drink?
4. Where is your location when you drink?
5. What do you drink?
6. Do you use the same hand when you drink?
7. When do you go to sleep?
8. When do you wake up?

Figure 28: Interview questions

APPENDIX D: INTERVIEW ANSWERS

Answer 1:
Age: 78 years
Gender: Female

1. It depends on the activity and what I have eaten.
2. Nothing special but I often drink 1 dl in bathroom before going to bed, sometimes I drink a little water if I have to go to toilet.
3. 11th of oct I drank 1,7 liters, that is 17 dl.
4. Most of it I drank in the kitchen.
5. I drank green tea, coffee, milk, juice and water.
6. I always use right hand when I drink.
7. Goes to sleep approx 23.30.
8. Wakes up 6.30 and goes up at 7.

Answer 2:
Gender: Male

06:00 - Went up
06.15 - 1 dl water in kitchen
07.00 - 1 dl milk in kitchen
09.00 - 2 cups of coffee in a social meeting in Rödeby
12.00 - 2 dl juice in kitchen
17.00 - 4,5 dl milk in kitchen
20.00 - 1 dl milk in kitchen
22:15 - Went to bed

Answer 3:
Gender: Female

1. I am almost always thirsty. Depends on my medication.
2. Thirst makes me motivated, know that even, that coffee is fluid dialectic (medical term for fluid out of the body, in Swedish vätskedrivande).
3. I drink when I go up and every second hour.
4. I drink water, juice, and milk.
5. I drink approx 2 liters per day.
6. I use the right hand, same hand when I drink.
7. I go to sleep as early as 22 in the evening I try to read, but I get my book in the head and falls to sleep.
8. I wake up at 7.00 in the morning. Have then slept for 9 hours.

Answer 4:
Age: 69
Gender: Male

- Use the same hand

12 October	13 October
Wakes up 6.30 Goes to bed 00.00 9 Breakfast, 1,5 litre file 1 dl coffee 1 dl water 11.30 1,5 dl coffee 14 lunch 2 dl juice, 2 dl " (probably juice?) 15.30 2 dl water 18 2 dl coffees 20 4,5 cider 1,5 coffee 2 water	Goes up 07.00-23.30 goes to bed 9 2 dl milk 1 coffee 2 water 14 2 juice 2 " (juice?) 15.30 2 water 18 2 coffee 20 5 water Use the same hand

Figure 29: Interview answers

APPENDIX E: ACTIVITY GRAPHS

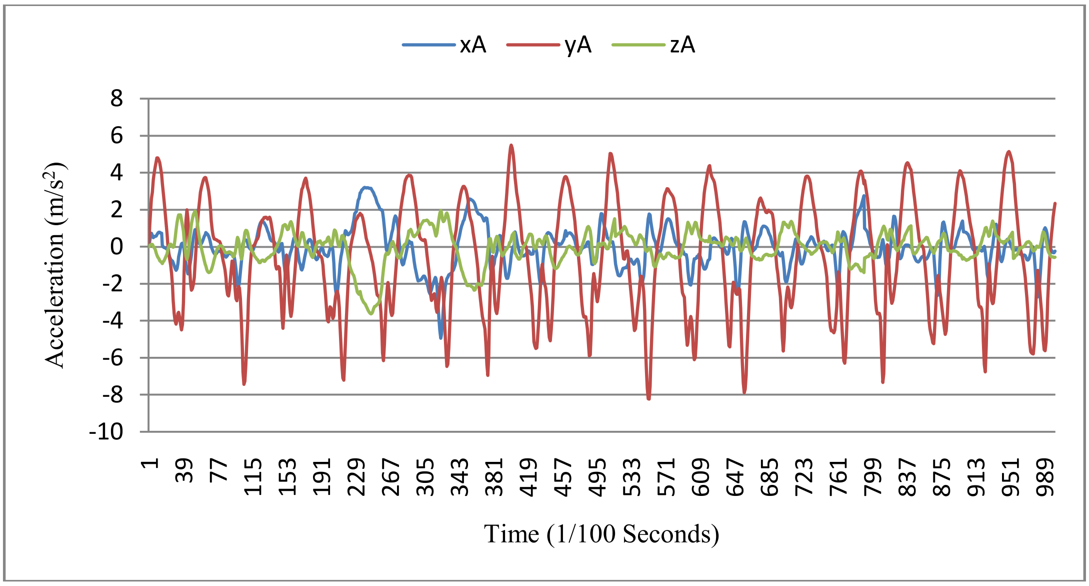

Figure 30: Accelerometer data (x, y and z) of Walking activity

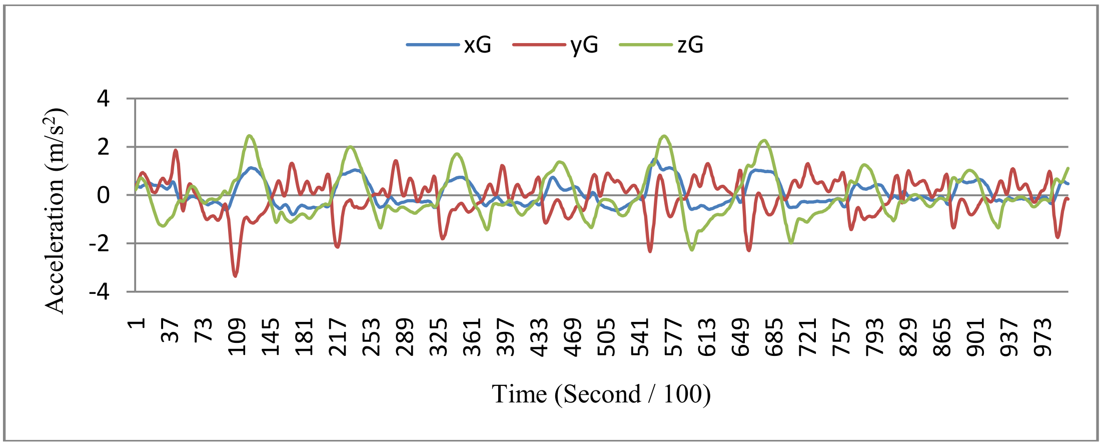

Figure 31: Gyroscope data (x, y and z) of Walking activity

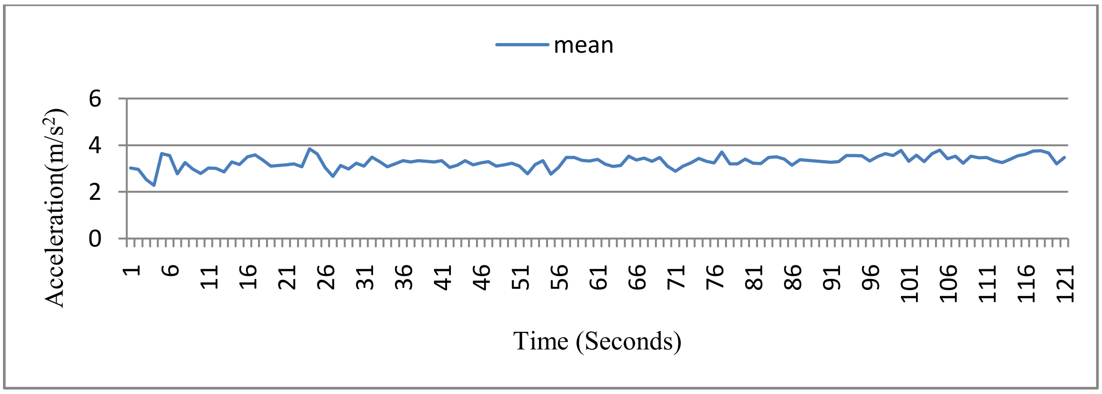

Figure 32: Accelerometer mean data of Walking activity

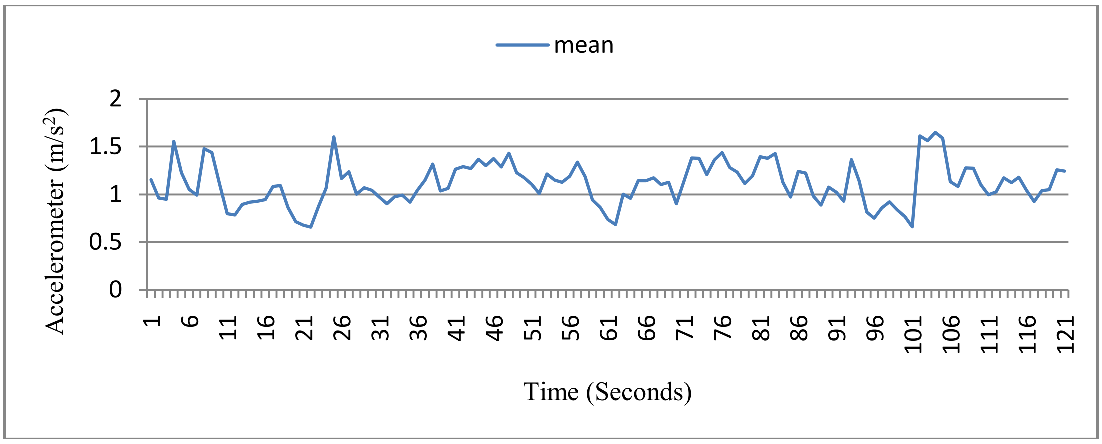

Figure 33: Gyroscope mean data of Walking activity

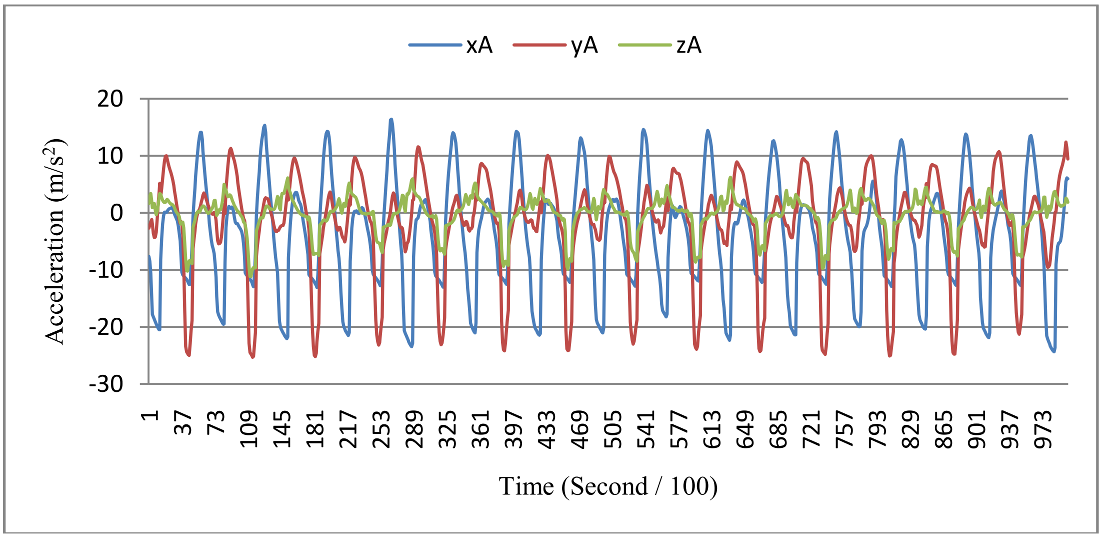

Figure 34: Accelerometer data (x, y and z) of Jogging activity

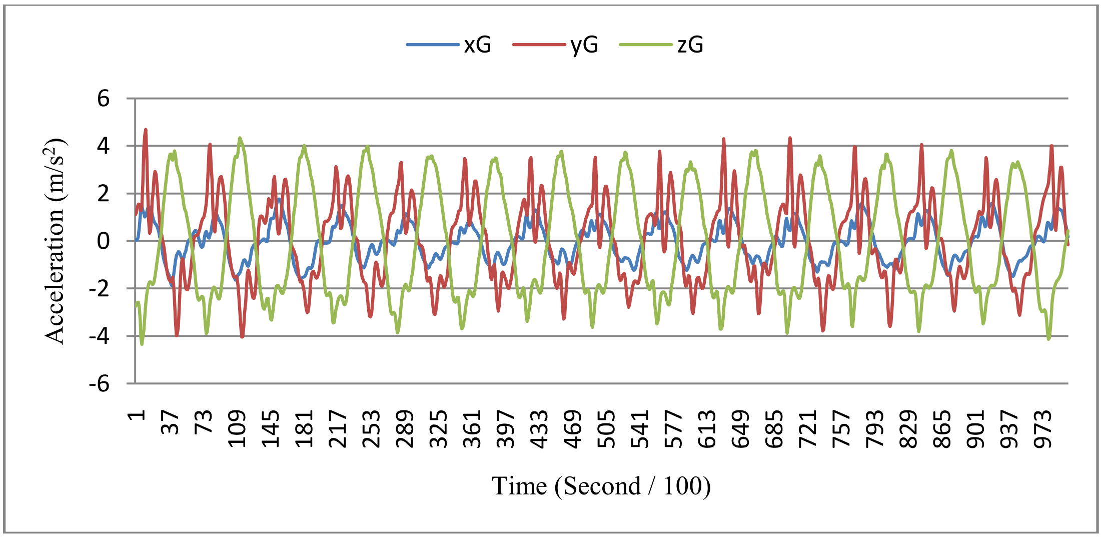

Figure 35: Gyroscope data (x, y and z) of Jogging activity

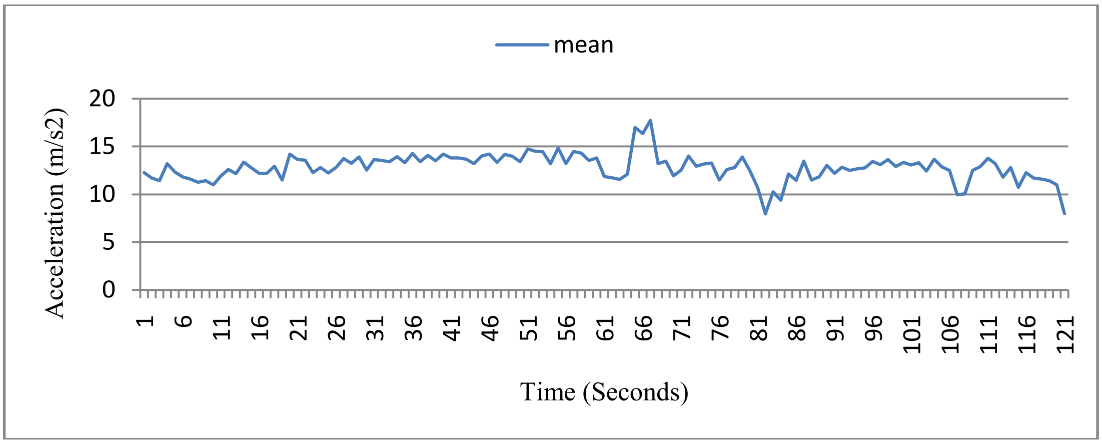

Figure 36: Accelerometer mean data of Jogging activity

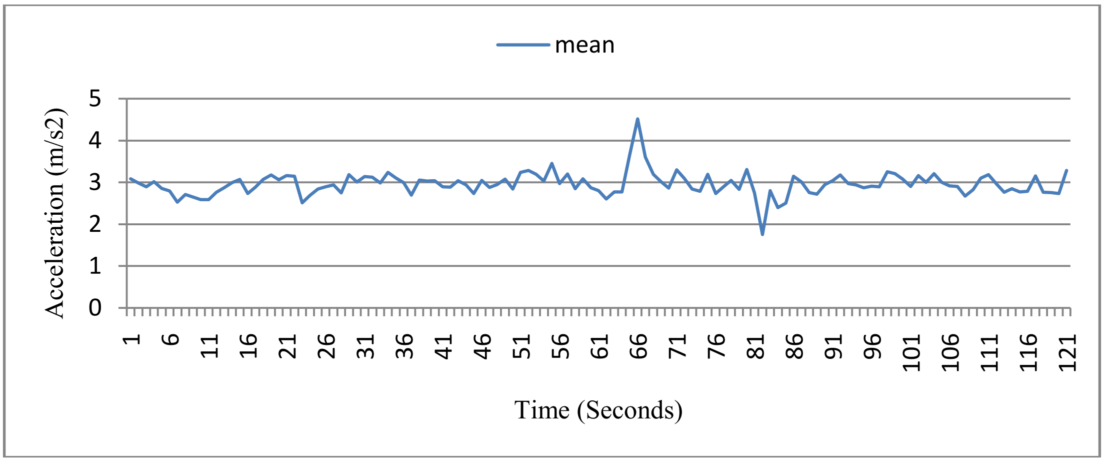

Figure 37: Gyroscope mean data of Jogging activity

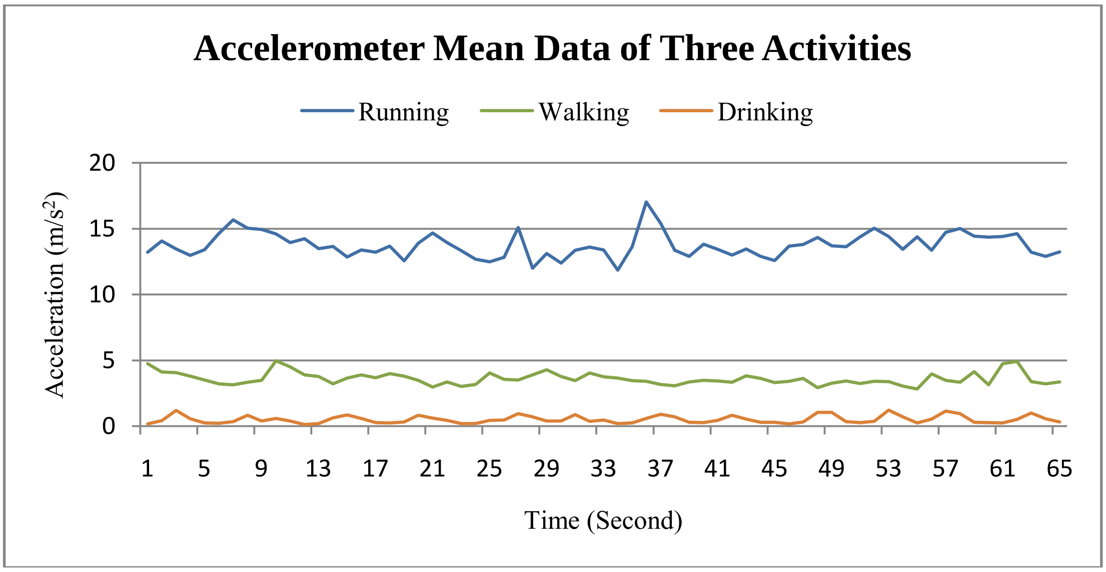

Figure 38: Mean values of Drinking, Walking and Jogging activities of accelerometer sensor

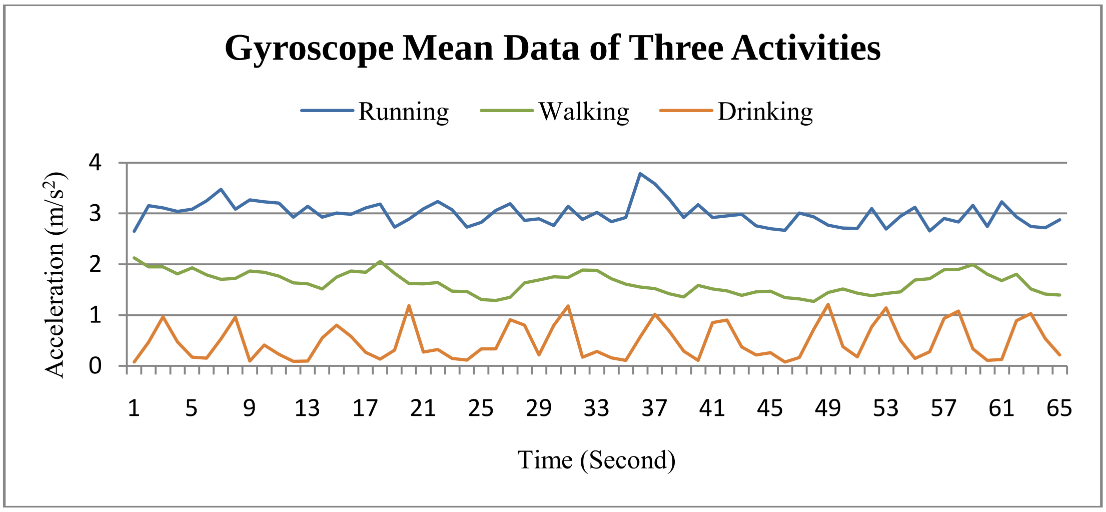

Figure 39: Mean values of Drinking, Walking and Jogging activities of gyroscope sensor

APPENDIX F: WEKA J48 CLASSIFIER OUTPUT

```
@relation evaluateJoggingWalkingDrinking

@attribute accelerometer    numeric
@attribute gyroscope    numeric
@attribute class    {Jogging, Walking, Drinking}

@data
1.195393771, 0.68617588, Drinking
13.87198285, 3.088028406, Jogging
0.998317994, 0.718473364, Drinking
13.69090581, 2.855158467, Jogging
0.815290913, 0.756834631, Drinking
4.286053865, 2.511542868, Walking
0.961303511, 1.069632493, Drinking
3.741501416, 1.815878841, Walking
0.881708687, 0.794894089, Drinking
13.05407932, 2.958112543, Jogging
1.049409316, 0.612201995, Drinking
14.16148069, 3.085881022, Jogging
.
.
.
3.985095474, 1.727434765, Walking
```

Figure 40: Dataset in ARFF format of Drinking, Walking and Jogging activity