Ubitrack: A Study on Lost Person Activity Estimation Using Accelerometer Data from Smartphones

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Ubitrack: A STUDY ON LOST PERSON ACTIVITY ESTIMATION USING ACCELEROMETER DATA FROM SMARTPHONES

By

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ABSTRACT

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As smartphones become very more popular, applications are being developed with new and innovative ways to solve problems faced in the day-to-day lives of users. One area of smartphone technology that has been developed in recent years is human activity recognition HAR. This technology uses various sensors that are built into the smartphone to sense a person's activity in real time. Applications that incorporate HAR can be used to track a person's movements and are very useful in areas such as health care.

In our research, we use this type of motion sensing technology, specifically, using data collected from the accelerometer sensor. The purpose of this study is to estimate the pilgrim who may become lost on the annual pilgrimage to Hajj. The application is capable of estimating the movements of people in a crowded area, and of indicating whether or not the person is lost in a crowded area based on his/her movements as detected by the smartphone. This will be a great benefit to anyone interested in crowd management strategies, specifically regarding Hajj.

In this thesis, we review related literature and research that has given us the basis for our own research. For example, we could not create this application without the use of HAR technology and without specific classification algorithms. We also detail research on lost person behavior. We looked at the typical movements a person will likely make when he/she is lost and used these movements to indicate lost person behavior. We then describe the creation of the application, all of its components, and the testing process. Finally, we discuss the results of our trials and plans for future work.

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CHAPTER 1: INTRODUCTION

This thesis is a part of the Ubicomp project at Marquette University, department of Mathematics, Statistics and Computer Science (MSCS)[1]. The study is funded by the Kingdom of Saudi Arabia. The purpose of this research is to provide new solutions to the issue of crowd management at Hajj [1].

Imagine a person who becomes lost while on the Hajj pilgrimage among upwards of three million people in Makkah. Each year, millions of people from all over the world make the pilgrimage to the holy city of Makkah and the number only continues to increase each year [2]. This is an important spiritual ritual, as it is one of the five pillars of Islam.

There is a large potential for research around this event, especially when it comes to lost person behavior. "Even though Hajj is one of the biggest and oldest events, still little is done to objectively monitor the pilgrims and to understand what makes this event extraordinary" [2:680]. People usually travel to Hajj with family and are mostly unfamiliar with the area. They are almost exclusively on foot and the areas become crowded. If a person becomes separated from the rest of the family, it can be very difficult to reunite.

When a person becomes lost in a crowded area, it is always a cause for distress for that person and for the friends or family from which the person was separated. The person may not know the area well and have a difficult time reconnecting with his/her family or friends or finding the way back to a known location. A person could become lost anywhere, but in this study we will focus on crowded areas where people travel on foot.

The area at Makkah is small, and the number of attendees increases year after year, which has created an ongoing and ever increasing problem of crowd management [2]. One specific issue, which is the topic of this thesis, is when people become lost in the crowd. Ground personnel are overworked already and it is costly to continuously hire more. We are looking for a more effective approach to this issue.

Our solution to aiding in the issue of studying and estimating lost persons in the crowd at Hajj is a smartphone application. The application is able to track a person's movements and activities right on his/her smartphone and display an alert on the screen if the person is displaying unusual behavior, specifically behavior that is indicative of a lost person.

The application is possible due to sensors that already exist in most smartphones. For our project, we uses an android smartphone. The sensors include: accelerometer, gyroscope, thermometer, barometer, etc. [3]. For this thesis, we used only the accelerometer sensor, but may include the use of more sensors in future work.

The field in which we are working is called Human Activity Recognition, or HAR [4]. In this thesis, we review several other research projects that incorporate HAR. It is a field that is growing because in the past all HAR technology used external sensors attached to a person's body [4]. However, now with the use of smartphones, the same technology is much more accessible and easily used in many research projects.

In order to create this application, we first looked at lost person behavior. What motions or actions would indicate that a person is lost? We looked at psychological studies as well as guidelines from search and rescue teams to understand what a person typically does when he/she becomes lost. We found several activities that indicate a lost person: running/jogging, falling down, and moving randomly in direction and also speed [5]. For example, a person who is running left, then walking right, then falling down would be displaying lost person behavior [5].

For our study, we included two normal movements as points of comparison. The application, via the accelerometer sensor in the android smartphone, is able to detect five motions: standing still, walking, running/jogging, falling down, and moving randomly. We then tested the application on each of these activities with human trials.

We found that certain activities had a very high rating of accuracy, while one did not have as high of a rating. To collect and analyze the data, we used ARFF and CSV files, which can be stored and used right on the smartphone, with no additional or outside platform needed. We used a decision tree algorithm, the J48, which is available through weka, and also able to run right on the smartphone [6][7]. We used classification and a cross-validation test to ensure that our results were accurate [8]. The thesis discusses each of these aspects in detail.

Finally, we chart and discuss our results and plans for future work. Overall, we were happy with the results and found that this application will aid in our overall goal of finding new a way of crowd management at Hajj. The idea of using a smartphone to track the movements of a lost person in the crowd is certainly viable, based on our results. The application that we have developed can indeed indicate whether or not a person is displaying lost person behavior.

CHAPTER 2: BACKGROUND

These days, almost all people carry a cellular phone with them [3]. “As handheld devices have been booming up in recent years, the usage of laptops, smartphones, and tablets is increasing exponentially” [9:1]. Our research aims to study and create a smartphone application that will take advantage of recent technology to indicate when a person becomes lost and will help that person to reconnect with family or essentially, to be found. This could be applied to any smartphone or device, but for the purposes of our research, we will be using an Android phone. The application is based on the use of an accelerometer sensor built into the phone [3].

The technology necessary is already widely available on most phones, along with other sensor technology such as gyroscope, GPS, light sensors, etc. [10]. The accelerometer will be able to detect movement and the application will then work to discern whether the movement is typical - such as walking in a normal direction - or indicative of a lost person - such as running or moving randomly [11]. In order to discern what is typical behavior versus lost person behavior, background research on the psychology of lost person behavior will be conducted.

If the behavior is indicative of a lost person, an alert will appear on the screen. In this way, the application can help families along with rescue workers and health care workers to relocate a person who has been lost in a crowded area.

2.1 Sensors for Detecting Human Activity

Sensors have been used in a variety of ways to detect human activity [9][10][11][12]. In recent years, chtenology has become more advanced, especially in the use of smartphone applications [10]. Human activity monitoring technology can be applied to a variety of fields, and also used for the average consumer product. However, it is most useful presently in the areas of healthcare and assisted living [11][12]. Sensor technology refers to software that can recognize and track human activity. Smartphones are an ideal platform for this technology as they already contain several sensors capable of detecting human movement, and are also capable of detecting location via mapping applications [13]. Millions of people carry a smartphone on a regular basis, so it makes sense to further develop sensor technology for a smartphone application [10][11][12].

Smartphones are becoming more and more advanced each day. People are scrambling to create apps for smartphones for everything from games to serious health applications. Smartphones themselves are now capable of more computing power, wider networks, faster speeds, and more data storage [3]. Companies work to improve smartphones and stay ahead of the competition. Smartphone technology has changed the way that most people operate on a daily basis [3].

Data mining applications can be used by companies to track people's patterns of behavior [14]. Some see data mining as an invasion of privacy, while others see the benefits to society that can come from understanding larger patterns of behavior. "We have made our data set and our data collection application publicly available, thereby making our experiments reproducible" [10:1]. The Shoaib study [10] points to one example of how data mining can be beneficial to researchers. Data applications can be used to monitor health and fitness, they can be used to assist in elder care, and can be used for location and navigation systems [12].

Human activity recognition is behind all of this technology. Applications that can detect human movement and location take a raw sensor reading and can then predict human motion and activity [10][15]. Most smartphones already contain the sensors necessary to detect human motion such as: accelerometers, gyroscope, GPS, light sensors, temperature sensors, etc. [3]. Typical activities that can be detected using a smartphone with these sensors include walking, jogging, sitting, etc. Motion sensors are already used for a variety of smartphone applications. “For example, a game might track reading from a device’s gravity sensor to infer complex user gestures and motions, such as tilt, shake, rotation, or swing” [3]. Due to the low cost of development, smartphone applications have become the leading technology used for human motion and activity recognition [13].

Activity recognition can be used in a variety of real life scenarios. It can also be linked to other applications within the phone, making smartphones even smarter [12]. “For example, suppose that the phone detects that the user is about to leave the room and its weather application indicates that it will rain later, a reminder will pop up with a message ‘Bring an umbrella. It is going to rain with a high probability’” [12:235]. In this manner, activity recognition technology can add to and improve existing technology. Activity recognition technology can also be used to improve navigation or mapping systems based on data mining trends. For example, if the data shows that many people take a certain highway during rush hour causing gridlock traffic, the navigation system can recommend an alternate route for the user. These are just a couple scenarios in which data collected from motion sensor technology along with GPS technology on smartphones can be used to develop beneficial applications.

Activity recognition technology is already being used for fitness applications. People can track everything from steps taken in a day to hours of sleep [16]. The data can then be analyzed to show a person's overall fitness level and recommendations can be made to the person regarding areas that need improvement. Fitness trackers such as Fitbit have become incredibly popular [12]. It is just one more example of successful use of motion sensor technology in smartphone applications.

Most importantly, activity recognition technology on smartphones can be lifesaving. Applications can be used in health care to monitor a person's behavior [13]. "Sensors can be used for understanding the user's activity which can provide us with contextual information about the user's present state" [13:1]. For example, sensors of this type can detect an elderly person's fall. The same technology could be used when working with children with Autism Spectrum Disorder, for another example.

Finally, applications can be created to locate people who become lost [2]. Human activity recognition technology is already readily available and can be used to detect the behavior of a person in motion. These motions can then be analyzed and compared to typical behaviors or movements in order to determine whether or not the person has become lost. This is the type of technology that can assist in finding a person who is lost in a crowded area.

2.1.1 Accelerometers

Currently, smartphone technology can sense a many aspects of data that can be combined and analyzed to get a picture of a person's movement patterns. "They can record users physiological states such as location changes, moving direction, speed, etc. Such sensors include accelerometers, microphones, GPS, barometers, etc." [12]. Sensors can detect everything from light levels to proximities [16][17]. However, for this research, the accelerometer is the most important sensor as it reads motions statistics [16]. The accelerometer will be used in the application to detect lost person behavior.

Accelerometers in smartphones can detect motion in three directions, which are predetermined from the axis. The g-force of the acceleration is measured in all three directions and then the raw data is represented as a set of three vectors (x, y, and z) Figure 1. These axes capture the horizontal movement of the user (x-axis), upward/downward movement (y-axis), and forward/backward movement (z-axis) [11]. MEMS accelerometers are quite advanced and can sense orientation, vibration, coordination, acceleration, and shock [15]. Additionally, a time stamp can be accessed simultaneous with the set of three readings. Current accelerometers have a user interface that will "configure the sampling frequency" so that users are able to easily access the data [12].

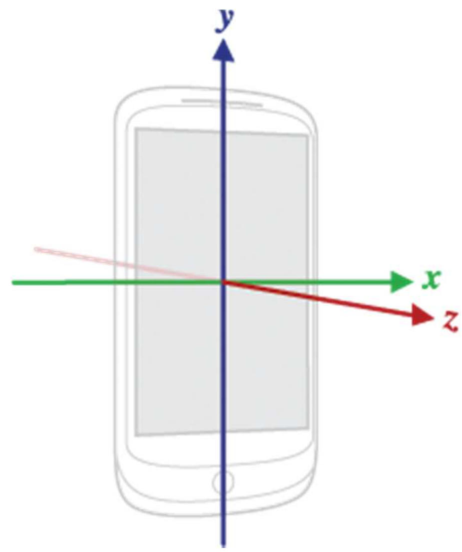


Figure 1. A 3-axis of accelerometer in smartphones [3].

Accelerometers are extremely popular and useful in motion sensing technology. They can directly measure the motion status and physiology of a subject. “For example, if a user changes his/her activity from walking to jogging, it will reflect on the signal shape of the acceleration reading along the vertical axis” [17:237]. Over a time period, acceleration data can indicate a motion pattern which is helpful in complex activity recognition. Accelerometers are widely used in automotive braking systems, vibration on cars, game controllers, airplane orientation, military weapon fire systems, and in laptops [15]. They can detect all sorts of complex motion patterns. This is the type of human activity monitoring technology that will be used to detect lost person behavior.

Accelerometer data can be collected very successfully with the use of a smartphone on the person. Wearable devices have been proven effective for monitoring and sensing human activity. “Casale et al. use a wearable device for collecting acceleration data for human activity recognition, obtaining 94% accuracy” [11:451]. Additionally, a smartphone is ideal for recording data as it is placed near the center of gravity. Thus, an accelerometer in a smartphone is a accurate method of recording human activity data [11].

2.2 Lost Person Behavior and Psychology in Crowded Areas

The psychology and typical behavior of a lost person in a crowded area can be useful in developing an application that will aid searchers in estimating the movements of the lost person. It is important to understand what typical behavior looks like so that searchers and family members will know when the person is behaving typically versus when the person is behaving abnormally, which would indicate that something more serious is wrong, such as a possible accident.

A large percentage of lost persons are found within a three mile radius of the place where they were last seen [18] [19]. The average person can walk about two miles every hour, however, they are likely to stay within the same area where they were lost, which indicates the Probability Zone [18]. This means that the person who is lost will be moving in many directions. They may go one direction, but then will turn back in another direction, thus staying within the Probability Zone of less than three miles [18].

The best method for a lost person to be found is for the person to stay where they are. However, most people do not stay put in one spot. "Many people will continue to wander to try to somehow save themselves" [18:1]. People who are lost often become fearful or even panicked. This can prevent them from staying put as fear can trigger a "fight or flight" reaction [5]. "Fear stimulates a heightened concern for self-preservation, mobilizing the body for flight through the secretion of adrenalin and increased blood supply to the legs. It's no wonder, therefore, that the lost person's impulse is to move rather than stay put" [5:11]. Although most people know that, statistically speaking, a lost person is more likely to be found if they stay put, people still sucumb to the urge to move.

It may seem logical to travel in one direction, but most people, when lost move around in a random pattern [5][20]. Some people will attempt to follow a trail or a familiar route, but research indicates that 62% of people will leave the trail [18]. "Totally confused, and usually experiencing high emotional arousal, the lost person moves around randomly, following the path of least resistance, with no apparent purpose" [5:8]. This indicates that people will move randomly when they are lost, not along a straight line such trial or clear route. If random movements are detected, it is an indicator that the person may be lost.

Another common response of lost persons who are attempting to find their way is known as route traveling or "trail running" [5][20][21]. The person finds some sort of trail or path and runs down the trail, but lacks a sense of direction. They could choose to go either way down the path. People will stay on a trail and continue to run even if they are not convinced that they are heading in the right direction [18]. "This is usually an ineffective method of reorientation, shown most often by school-aged children under 12 years of age" [5:8]. The behavior of running in a linear pattern, but not necessarily the right direction, is therefore another indicator of lost person behavior. If the sensors are able to detect that the person starts to run or jog, seemingly at random, this would be a good indication that the person is lost and is exhibiting typical lost person behavior.

Another behavior that may indicate a person is lost is called "view finding" [5][22]. The person will move around in attempt to find a better view of the area. "The lost person attempts to gain a position of height in order to view landmarks in the distance...by climbing a hill, ridge or tree" [5:9]. This movement can create a random path of travel; not following a path or logical direction. "Many people will ignore a trail and follow their own logic based on line of sight" [5:2]. In a crowd, the person would move left, right, forward, and backward in attempt to see around or between the people of the crowd. The person would be attempting to see past the other people who are blocking the view in front of him in an effort to catch a glimpse of his family members or other members of his travel group. Therefore, if the accelerometer sensors pick up a random pattern, that would indicate that the person is moving in a way typical to a lost person who is perhaps attempting to find a view.

Finally, if the accelerometer application senses that the person has fallen down, that would indicate not only that the person is lost, but also that the person may be in some danger such as a health condition. Even though most people who are lost will travel rather than staying put, by the time that they are found, especially if the search lasts more than 24 hours, the person is usually found in a stationary position [5][21]. "This is usually because they are fatigued, asleep, or unconscious" [5:10]. The longer the person is lost, especially after 24 hours, the greater the danger becomes.

An example of a person who may have health issues is an elderly person with Alzheimer's Disease. However, these people, like other lost people, follow some predictable patterns of typical behavior. If the person has been lost more than once, they can establish patterns of behavior specific to that person. In fact, 70% of people with Alzheimer's Disease will wander at some point and 83% of those people who are lost are repeat cases [18]. In general, these people are found in the immediate area - 50% are found 0.6 miles of the last point seen and 96% 1.5 miles [20]. They may not respond to searchers and may not even realize that they are lost [18]. Finally, "most are elderly, less capable of self-care, and will more easily succumb to issues in the environment" [18:5]. A person with such health issues may be prone to falling down and this would indicate a behavior of a missing person. Therefore, if the accelerometer sensor indicates a fall down, this behavior should be considered an important indication of a potential health issue, especially if the person has a history of known health issues such as Alzheimer's Disease.

2.3 Risk of Lost Person

Whenever a person is lost, some type of action is required. There are many risks associated with becoming lost - it can be a dangerous situation. Even if the situation is not a medical emergency, the lost person can experience fear and panic, so it is important to find the person as quickly as possible [18][19][20][21].

Children are at a greater risk when they become lost. Children age 1-3 years may be unaware of being lost and therefore wander aimlessly. They are therefore very difficult to detect [21]. At this age, a child is not capable of finding his or her family alone and will need the help of an adult, such as a police officer or rescue worker. This group is obviously at a high risk because they are very young.

Older children, age 7-12, are also at a higher risk. Children of this age are much more likely to become confused and upset, even panicked, when they realize they are lost [21]. They frequently resort to "trail running" meaning to run a long distance on a straight path, and can travel much farther than younger children in this way [20][21].

Another group at high risk are elderly persons with dementia. Another group are called “walkaways”[5]. These are people who do not understand that they are lost and simply wander away. This group is at particularly high risk because they are very unaware of their surroundings and their situation [5].

Other risks to all lost persons include being exposed to bad weather, possibility of injury, becoming lost after dark, and becoming dehydrated. People who become lost generally are not planning to spend an extended time outdoors and are not prepared for the weather [5][19][20][21]. It may seem like just an inconvenience, but there are real physical risks to a person who becomes lost in an unfamiliar area.

CHAPTER 3: MOTIVATION

In developing this system, our major motivation is to monitor and estimate lost person behavior. Travelling can be a very stressful time, especially if someone is unfamiliar with the area they are travelling in. To further explore our motivation, we offer the following scenarios that we hope to help others avoid by using our application.

This research is part of a project funded by the Kingdom of Saudi Arabia which is working to find a better system of tracking pilgrims during the Hajj. It is being carried out through Ubicomp Lab at Marquette University [1]. The yearly pilgrimage to the Muslim holy place of Mecca attracts millions of people, and the number continues to grow each year. Crowd management has increasingly become a problem, therefore many people are researching solutions to this issue. Using personnel on the ground has become completely insufficient due to the sheer volume of people in the crowd [23][24]. Moreover, it is expensive to employ so many people to attempt management from the ground level in this situation [23]. our research on lost person behavior and locating lost persons in a crowded area via a smartphone tracking device is a direct solution to this problem. It is meant to be directly applied to the city of Mecca during the pilgrimage.

The following are three examples of issues that are commonly faced by people during the pilgrimage. Unfortunately, they are very common situations and currently have no good solution. All three situations relate to lost persons. Also, all three can be resolved much more easily with the technology that we are proposing - the smartphone application for tracking lost person behavior.

The movement patterns of a person who is lost can be tracked via the smartphone application. Wherever the person takes the phone, the application will be tracking their movement and constantly recording and analyzing the data. This data can then be used to determine if the person is following a normal or abnormal pattern of behavior that would indicate that the person is lost and in need of assistance. It can be linked to a mapping application and use GPS to locate the person. When reading the three scenarios, keep this application in mind. It is clear to see how it would be valuable in each situation.

3.1 Scenario 1: Where am I?

For a first time traveler, or even a seasoned traveler, it is easy to get lost in an unfamiliar city. This issue is further complicated if there are large crowds. Imagine a crowded city street in Mecca during the Hajj when millions of pilgrims visit at once. During the time of pilgrimage, there can be 4 million people in an area that is only 460 square miles [24]. Another example may include visiting Kampala where there are large crowds of people on foot and no street signs or landmarks to show direction. Or, as another example, imagine finding your way around Tokyo where the signs are all in Japanese. It is the most densely populated area in the world, not to mention a huge tourist destination, attracting people from all over the world. In any case, finding your way in a large, unfamiliar, crowded city is a challenge for any traveler. For the purpose of this case study, we will focus on the crowded area of Mecca, as in the project.

Each year, more and more pilgrims travel to Makkah and Madinah during the holy time of the Hajj and Omra. The space is limited, which means that more and more people are fitting into the same space. People come from all over the world, which means that they are not familiar with the area. Even if they come year after year, it is still difficult to remember directions in an unfamiliar city.

There are many factors that lead a person to become lost. In this experiment, the factors we will focus on include crowded areas, densely populated areas, or areas with many tourists. Another factor that could add to the situation is poor visibility, such as limiting visibility to the street level with no elevated levels. Poor mobility is an additional consideration.

For this experiment, we will imagine a person traveling on foot with little to no knowledge of the area. For example, a tourist who has just landed in Mecca, checked into a hotel, and then gone to look for a restaurant on foot. The person does not have a map, has no knowledge of the transportation system, or the street patterns. The streets are crowded and the land is flat leading to poor visibility. The person may have a difficult time finding a restaurant, then finding his or her way back to the hotel. If the tourist makes a wrong turn, he or she may quickly become lost.

In fact, the same assumptions for the experiment could even apply to a very familiar area. For another example, we could imagine a person who is attending an event such as visiting Mina, Arafat, Muzdalifah, Ramy al-Jamarat, and Al-Haram mosque. Let’s say the person is from Mecca and very familiar with where she is going. However, when she gets to Al Haram, she leaves the area to find a bathroom and becomes disoriented because there are so many people. It may take the person quite a while to figure out where she is, figure out directions, and find her way to the area where she intended to go. This is because the large crowds can easily block the view and cause disorientation, even in a familiar area.

3.2 Scenario 2: Where are my family members?

Usually, people travel with at least one other person, often a family member. It is also common for an entire family to travel together, or a group of friends to travel together. One of the biggest challenges of traveling in a group is keeping the group all together as you move from place to place. It is very common in crowded areas that family or group members may wander apart due to numerous reasons. If there is a huge moving crowd, it can be nearly impossible for the family or group members to re-unite. This could be a dangerous or frightening situation, which will be discussed in scenario three, but mostly it is just a lot of time wasted and a lot of frustration and stress spent looking for a missing member of the family or group. Therefore, knowing the location of family members is a great benefit which will not only save the time of everyone involved, but also relieve the stress on the lost person as well as his or her family or group members.

A good example of this would be a family traveling to Mecca together. It is almost inevitable that at some point the family will become separated. Perhaps they even do it purposefully. A family member could need to use the bathroom, become tired and tell the rest of the family that he/she is going to rest and then rejoin the group later, or want to stop for some food. These are all examples of how family members commonly and easily separate from the rest of the family. It is almost impossible that they would be able to reunite the group once becoming separated in such a huge, moving crowd. The family would soon become worried about the missing person or persons and would spend a great deal of time and energy trying to find them, essentially wasting all of their time trying to locate the person. Such a situation can lead to a lot of stress, and what was meant to be a nice time with your family can quickly turn into a tedious search, which makes it a very bad experience for everyone involved.

3.3 Scenario 3: My father is lost. He is elderly and has a heart problem.

The situation gets worse when the lost person is a senior family member, a child, or someone who has an illness. It may seem like an extreme situation, but unfortunately, it is not at all unusual for a family to lose an elderly father or mother in a crowded area. Children also frequently become lost because they are easily distracted and wander off. Additionally, any person, but particularly elderly persons may need medical attention. The situation can quickly become an emergency situation due to any of these reasons.

If the person has a medical condition, such as a heart condition, it adds several layers of complication. First of all, the lost person may be in great danger. He or she may know this and become extremely stressed or panicked, which can lead to an even worse situation. Secondly, the family members looking for this person would also be very stressed and worried as they attempt to find the person before he or she becomes ill. Finally, it is very difficult for medical staff to deal with such a situation. If the person has to be transported by ambulance, it would be complicated for the medical staff to reunite the person with his or her family members in the hospital or medical unit.

3.4 Characteristics of System Software

The objective of this project is to help people in situations similar to these scenarios. The three scenarios may seem extreme, and very stressful, but in fact they are very common. Hundreds of people each year deal with these exact situations when traveling to the Hajj [23][24]. These common situations involving lost people come with a high cost. First of all, such situations cause extreme stress for both the lost person and the family members who are trying to locate him or her. Secondly, much time is wasted looking for the person. Third, people who attempt to help the person and aid with crowd control are needed more and more each year, leading to high cost of staffing [23]. Finally, if the person needs medical attention, the situation becomes even more complicated as medical staff try to locate the person, aid him or her, and then also to reunite the person with the family.

All of these problems arise more and more each year. Thus, new technology is needed to quickly and easily track the behavior and movements of a lost person in a crowded area [1]. The smartphone application is meant to help in these exact scenarios, and other similar scenarios as well [1]. The use of the application may also be extended to apply to other situations and in other cities with a similar issue of lost persons in crowded areas.

The goal is to create an application that helps people with:

• Recognition of various activities

• Estimation of the behavior of the lost person

• Detection of a person who might be lost very quickly

• Avoiding medical emergencies

CHAPTER 4: RELATED WORK

4.1 Sensors for Detecting Human Activity

Our thesis project is based on previous research on the topic of human activity recognition (HAR). The earlier research on this topic revolved around wearable devices. Also, the earlier models were dependent on external hardware to analyze the data [16]. Casale et al. used a wearable device to obtain 94% accuracy in human activity recognition based on accelerometer data [16]. Nishkam and Nikhil used a triaxial accelerometer to track human activity, and focused on differentiating between eight separate activities or movements [25]. They found that certain activities had a high accuracy of recognition, such as standing versus running. Certain activities has a lower rate of accuracy - they were difficult to distinguish - such as running up the stairs versus running down the stairs [25]. All of this research was based on a device placed externally on a person and the use of an external or additional platform to analyze the data collected from the device.

The use of accelerometers has allowed researchers to develop human activity recognition technology (HAR). Accelerometers and microphones were used in a recognition system developed by Lester et al. [26]. Manniani and Sabitini proposed using multiple accelerometers along with separating the dynamic motion component from the gravity components, which led to a high level of accuracy in accelerometer data [27]. Casale et. al. studied movement pattern recognition from accelerometer data, also using a wearable, external device [16]. The device is a basis for activity recognition technology.

Current research on the topic of human activity recognition is now focused on the use of smartphone technology [11][17][28]. The study of HAR by Bayat et.al. focused on the use of accelerometer data from smartphones [11]. The accelerometer is a built-in feature of many modern smartphones and researchers have seen the opportunity to use this feature for HAR. Bayat et. al.[11] used an Android smartphone, just as in our research. They tracked human activities such as: slow versus fast walking and running up stains versus running downstairs. The accelerometer on the Android smartphone enabled the Bayat study to run a similar study to Nishkam and Nikhil, but instead of using an external device attached to the person, the Bayat study used the triaxial accelerometer which is built into the person's smartphone, carried in the person's hand [11][25]. Ghosh and Riccardi [13] also researched the use of HAR connecting it to smartphone technology. They presented their findings at the International Conference on Multimedia in 2014 which has contributed to the overall trend of connecting HAR technology to Smartphone technology sensors (accelerometer, gyroscope, etc.) [13].

Two studies serve as examples of work directly related to tracking pilgrims during the Hajj. Mantoro et. al. [23] studied tracking and monitoring systems currently in place. They give several examples of how modern technology can be better utilized for crowd management. The Mantoro study points to technology such as video surveillance and tracking. Muaremi et. al. [24] studied pilgrims as well. This study specifically used smartphones and wearable devices. The Muaremi study is an example for our own study. The objective is very similar. In the Muaremi research the objective was to monitor and understand the movements of pilgrims [24]. Our research is also monitoring patterns of movements and pilgrims, but it is more specifically focuses on the behavior of pilgrims who become lost in the crowd. Our research will only focus on the use of the smartphone technology, not on the comparison of smartphone technology and wearable devices, such as accelerometer, as in the previous studies [23][24].

The computing power of smartphones has greatly increased, so now computing and analysis of the data can be done right on the processing platform of the phone. No additional platform, such as an external server is necessary [11].

Many projects are similar to our own in the use of sensors to detect and monitor human activities. It is interesting to note that the same technology is used to track the movement of animals, for example, endangered species [29][30][31]. Several studies apply activity recognition technology in novel ways when looking at animals, however, it does not directly apply to our study, as our research will focus on humans.

Our research focuses on a specific area of human activity recognition technology for a very specific use. Most of the prior research uses HAR to detect daily activities (up/down stairs, walking, etc.). Our research is focused on detecting a very specific type of activity that would not occur in daily life, but would occur in a special circumstance - lost person behavior. We will use the prior research on HAR and apply it to detecting behaviors specific to lost persons. This technology will help to prevent potentially dangerous situations.

4.2 Lost Person Behavior and Psychology in Crowded Areas

In order to apply our research to meet the objective, it is necessary to study the behaviors of lost people in crowded areas. Previous research gives a basis of everyday activities tracking using HAR technology. However, we need to study abnormal activities, specifically the activities that can indicate that a person is lost.

Previous research on lost persons is mostly focused on search and rescue [20][21]. It did not have the goal of developing a smartphone application to detect the behavior of the lost person. However, the previous research does give many insights that are valuable in recognizing how a person who is lost is likely to behave. The main resource used in our research to gain the necessary background knowledge is “Lost Person Behavior” by Kenneth Hill [35]. Hill studied the psychology that underlies the behaviors that people exhibit when they become lost. Although each person is individual, there are many similarities that stem from human nature and psychology, that most people will exhibit when they become lost. For example, it is best for search and rescue teams if the lost person remains in one spot [5]. Hill discovered that contrary to this advice, people very rarely stay in one spot when they become lost; they feel compelled to move and try to find their way back [5][20].

Much research exists concerning search and rescue of lost persons. Koester [19] presents a guide for locating lost people - a search and rescue guide. Kelly [122] is another example of a search and rescue guide, which focuses on searching in urban areas, as opposed to a general search. This research [19][22] is very useful for gaining background information about lost person behavior, but does not directly relate to the development of the smartphone application. The research on search and rescue also does not focus on people who are lost in a crowded areas; they are more general information about lost persons.

Our research will combine what we know about the behavior of lost persons in a crowded area with the HAR technology that is already present, along with the use of the accelerometer built into an Android smartphone. Each of these aspects is present in previous research. Our project will combine all of these aspects into a single application that will accomplish the main objective of detecting when a person becomes lost in a crowded area at the Hajj, based on HAR technology.

4.3 Risk of Lost Person

There is currently no research that directly quantifies or studies the risks present to lost persons in a crowded area. It is especially difficult to quantify aspects such as emotional stress to the lost person and the family, and the risk of potential health risks, as opposed to actual incidents. Yet, it is clear that there is both physical and psychological risks to a person when he or she becomes lost [35].

Researchers in the field of medical applications have long been aware of health risks. Many applications are already on the market that focus on monitoring a person's physical activities with the intent of preventing health issues [13]. These applications usually focus on one specific health risk, whereas our application will be useful for a more general sense of health risks. Also, most current applications require manual input and monitoring of the data on behavior. Our application will monitor activity and assess the risk in real time. The data analysis will be done right on the smartphone, streamlining the process of risk analysis and HAR monitoring.

4.4 Algorithm

Several related works [10][11][17] have used different types of algorithms to analyze and synthesize data. For our study, we used Decision Trees Algorithm. This algorithm has several types of algorithms within the system, but for our research we used just the J48 algorithm. Other researchers who are also studying HAR and analyzing the data have chosen to use a variety of available algorithms such as Random Forest, Reduced Error Pruning, LogitBoost, Bayes Network-Nearest-Neighbor [32]. These are all examples that can be used. For our research, we had to choose which algorithm to use and chose the J48 Decision Tree. We found that this algorithm was the most accurate for our purpose, based on the cross-validation model [33]. Also, the output source code generated from J48 is in Java which works well for our purposes [33].

There are several data mining methods to choose from. Han and Kamber discuss different models for machine learning [14]. The paper by Quinlan discusses machine learning through the use of Decision Trees which allow the user to input multiple data sets [934]. Korting et. at. also discuss the use of Decision Trees, specifically multivariate [35].

Bhargava et. al. [33] explain data mining and weka, which stands for Waikato environment for knowledge analysis. Weka is freely available online and is developed by the University of Waikato in New Zealand [36][37]. This system allows users to freely access machine learning algorithms and state of the art data mining systems [37]. Data mining allows a user to extract useful information from a large volume of data. Various techniques for data mining are available on weka including: association, filtering, clustering, classification, regression, summarization, etc.[20]. Many researchers

[7][10][14] use weka in their projects because it is free, easy to use, and provides a variety of options or techniques.

J48 is a specific decision tree algorithm which was developed by Ross Quinlan [33]. It is commonly used for activity recognition research. The decision tree algorithm, with classifiers J48 can be executed on a workstation platform, or right on a user's smartphone [33]. For our study, we chose to streamline the application by executing the algorithm right on the Android smartphone.

Some of the related research projects have evaluated very similar data sets using a variety of classifiers. Bayat et. al. [11] used Multilayer Perceptron, Random Forest, LMT, SVM, Simple Logistic, and LogitBoost. They used the same data and ran all of these classifiers. The study found that Multilayer Perceptron had the highest level of accuracy. They also found that combining several classifiers can improve accuracy, efficiency and robustness of the data mining [11]. For our research we have decided to use a single classifier due to time constraints. Given unlimited time, it would be a good idea to run several classifiers to increase the accuracy of our findings.

CHAPTER 5: DATA COLLECTION AND ANALYSIS

5.1 Overview

The overall goal when collecting and analyzing the data is to recognize patterns that will indicate the physical activities of a person carrying the Android smartphone. The goal is to label activities based on the analysis of the accelerometer data which include: standing, running, walking, jogging, and moving randomly. Next, we aim to recognize and differentiate certain activity patterns - running/jogging, moving randomly, and falling down - from the other activities on the premise that these specific motions simulate the typical movements of a person who has become lost. In order to analyze and synthesize the data, we developed a sensor data collection application dedicated to this research. The system has been designed and implemented using four steps - data collection, feature selection, classification, and recognition of activity - as shown in Figure 1.0.

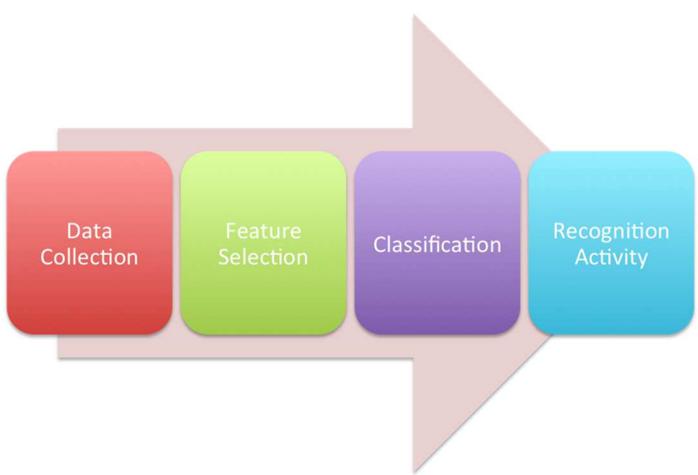


Figure 2.0: Steps for Human Activity Recognition

5.2 Data Collection Application

Smartphone sensor (accelerometer) data was recorded using the data recording application.

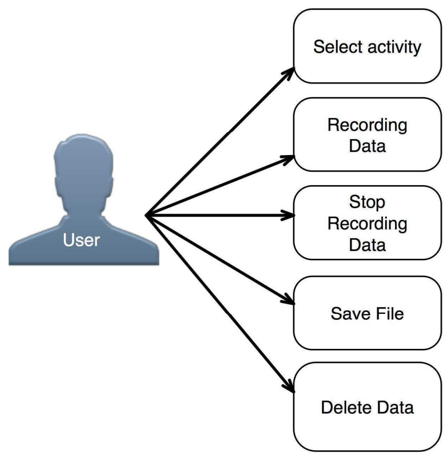


Figure 3.0: Use Case of User Activity Recorder

We followed a smartphone-programming tutorial from Dartmouth [38]. The accelerometer sensor data will be recorded using an Android application that we have developed called “Collector Tool.” “AndroSensor” is another tool we used for collecting data which is available through the Google play store [39] Figure 3.0. The graphical interface of the application has two parts shown here:

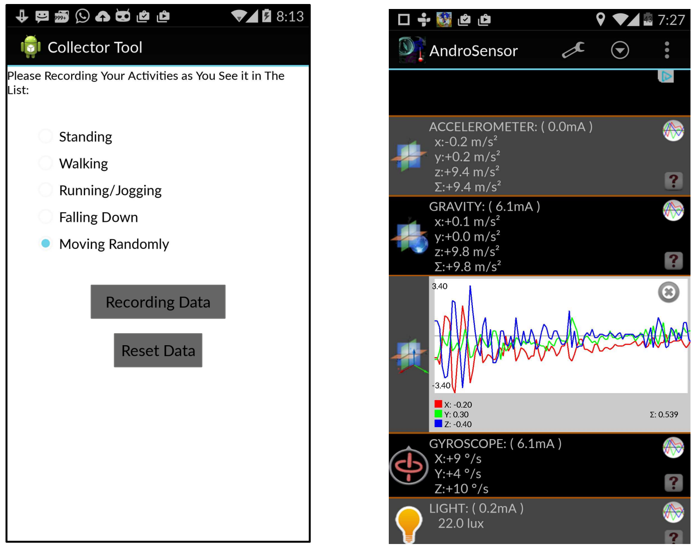


Figure 4.0: Interface of the Android application to record sensor data "Collector Tool" and "AndroSensor" [39]

Part 1: The interface displays five activities: standing, walking, running/jogging, falling down, and moving randomly. The user can scroll between these activities.

Part 2: This application contains two buttons - "Recording Data" and "Reset Data" - which are used to control the recording of the data. When the "Recording Data" button is pressed the application will start collecting and recording data, and the "Stop Recording" button is then pressed to stop the recording.

When the "Stop Recording" button is pressed, the "ColletorData" file is automatically saved. The "CollectorData" file will be automatically updated when the "Recording Data" button is pressed again. When the "Reset Data" button is pressed, the "CollectorData" file will be deleted. Further in this study, we will analyze the "CollectorData" file using the WEKA (Waikato Environment for Knowledge Analysis) [36] machine learning toolkit.

5.3 The Collection File

ARFF (Attribute-Relation File Format)and CSV were used to record activity data. ARFF is an ASCII text file which consists of a list of instances that share among them a certain set of attributes [36]. The CSV and ARFF file data were read and analyzed using Matlab, Microsoft Excel, and WEKA [6]. The files can be read without technology assistance; they are human readable. A snapshot of a sample data file is shown in Figure 4.0. The first row of the CSV file is the header which labels the sets of data that will be recorded. The CSV header consists of four labels: s, xA, yA, and zA. The ARFF file consists of two sections: a data section which contains the magnitude value and a header section. All section and label definitions are provided here:

- ACCELEROMETER X (m/sÂ²)
- ACCELEROMETER Y (m/sÂ²)
- ACCELEROMETER Z (m/sÂ²)
- (xA)(yA)(zA)= x, y, z axis data of accelerometer sensor
- s = m/sÂ² stands for the time in milliseconds
- The magnitude of the acceleration of each of the vectors can be calculated using the formula (5.8): for a vector i, magnitude of acceleration mag$i$. [10][16].

$$mag\imath = \sqrt{x^2 + y^2 + z^2} \tag{5.8}$$

	A	B	C
1	ACCELEROMETER X (m/sÂ²)	ACCELEROMETER Y (m/sÂ²)	ACCELEROMETER Z (m/sÂ²)
2	-2.0846	1.8569	8.6567
3	-1.4883	2.1521	8.3782
4	-1.2955	1.3094	10.0575
5	-0.6444	1.5463	9.0911
6	-0.7754	1.6093	8.7638
7	-1.574	1.3118	10.2741
8	-0.3636	1.5998	8.6674
9	-0.7944	1.2237	9.7969
10	-0.4707	1.3142	9.6981
11	0.3613	1.244	9.2946
12	-1.2979	1.8712	8.0163
13	0.1447	2.0021	9.5505
14	-0.4671	1.7236	9.1601
15	-0.8706	1.7641	8.9149
16	-0.2469	1.8771	9.466
17	-0.3636	1.9628	9.1066
18	-0.3755	2.0854	8.7328
19	-0.2779	2.1675	8.903

Figure 5.0: Data sample of walking activity; CSV and ARFF format.

5.4 Data Collection Procedure

After the development of the application for the Android smartphone, the next phase of the study involved collecting data with the use of the application. Three devices, all of which are operated by Android, were used in this study: Samsung Galaxy S3, Nexus 5, and OnePlus One. These three devices were used to collect data throughout the experiment. Four members of Ubicomp Lab at Marquette University [1] were used to collect the experiment data. The subjects ranged in age from 24 to 30 years old. All three devices were held horizontally in the palm of each subject's hand during the experiment (Figure 5.0). Five types of activity were recorded with experimental data including: standing, walking, running/jogging, falling down, and moving randomly.

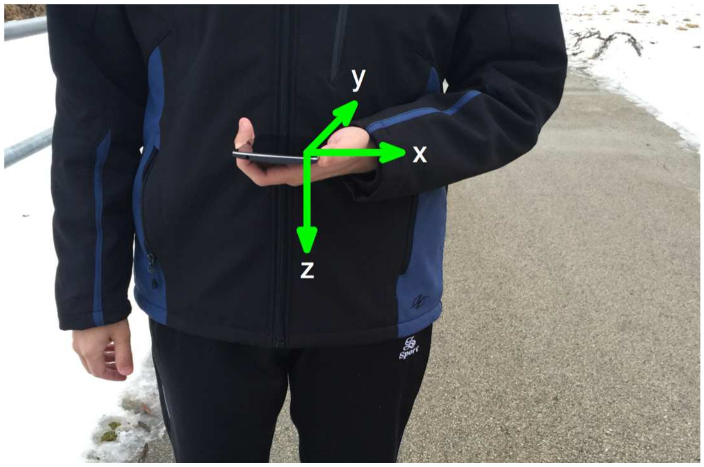


Figure 6.0: Smartphone placement on the hand palm

Each experiment type was documented at the beginning of data collection. Different environments were used for data collection depending on the type of activity recorded. The activity of falling down was performed in each subject's home environment, and data collection for this activity also took place in the subject's home. Data for walking, running and jogging was collected outside of the home environment in nearby places such as roads and parks. For these activities, data collection took place on site, wherever the experiment was conducted.

We led the subjects through each activity to ensure that the data was collected correctly and that the entire process ran smoothly. This was especially important for the final activity - moving randomly. Any activity recognition system needs to be able to generalize activity based on previously recorded data and apply that generalization to new subjects that it has never seen before. It should not only recognize activities and users that have already been tested, but be able to recognize any new user repeating the same types of activities.

The basic assumption behind the experiment is very important. This assumption is that in crowded areas, the subjects should be walking and moving together. Therefore, if the person displays any of the other activities - running/jogging, moving randomly or falling down - the system will detect this activity. Our main hypothesis is that the system will be able to differentiate between each activity; then we will classify according to normal behavior or movement versus behavior and movements that would indicate a lost person.

The final activity, moving randomly, was difficult to perform accurately in our environment since we are not living in a crowded area. Therefore, we tried to replicate the activity by imagining a scenario. The scenario was based on my experience at Hajj and Omra where I lost my family among three million other pilgrims. The experiment participants recreated the experience of moving randomly in a very crowded area like one would find at Hajj using alternative solutions to record an accurate replication of this type of movement.

There are 3 ways to do this activity:

1- The participants could watch a crowd moving on video. They would use the mobile device before and while collecting the data. Or, a device which supports Virtual Reality (VR), such as Samsung Gear VR (Figure 6.0) could be used while collecting the data to virtually simulate a crowded area. However, VR technology is very expensive.

2- The participants could go to a real crowded area such as Time Square in New York City or Makka for collecting the data. However, we did not have the time or resources to travel for this experiment. We will run the experiment in an actual crowded area this summer when we will visit Makkah to test the application.

3- We could recreate an activity to simulate the movements of a person who is lost in a crowded area. This is the way we chose to perform the activity. We drew a small map showing the path of a person moving randomly. This map represented a person who lost their family and was attempting to find them in a crowded area (Figure 7.0). To perform the activity, we used my building basement to create a small simulation of crowded area environment (Figure 8.0). Sixteen objects were used as obstacles - representing people standing and walking together - to replicate the crowd. The participants, holding the smartphone, then attempted to move past these obstacles moving right, left, forward, backward, and rotating around and through the crowd. For accuracy, the obstacles were changed several times during data collection.

Figure 7.0: *Samsung Gear VR Device*

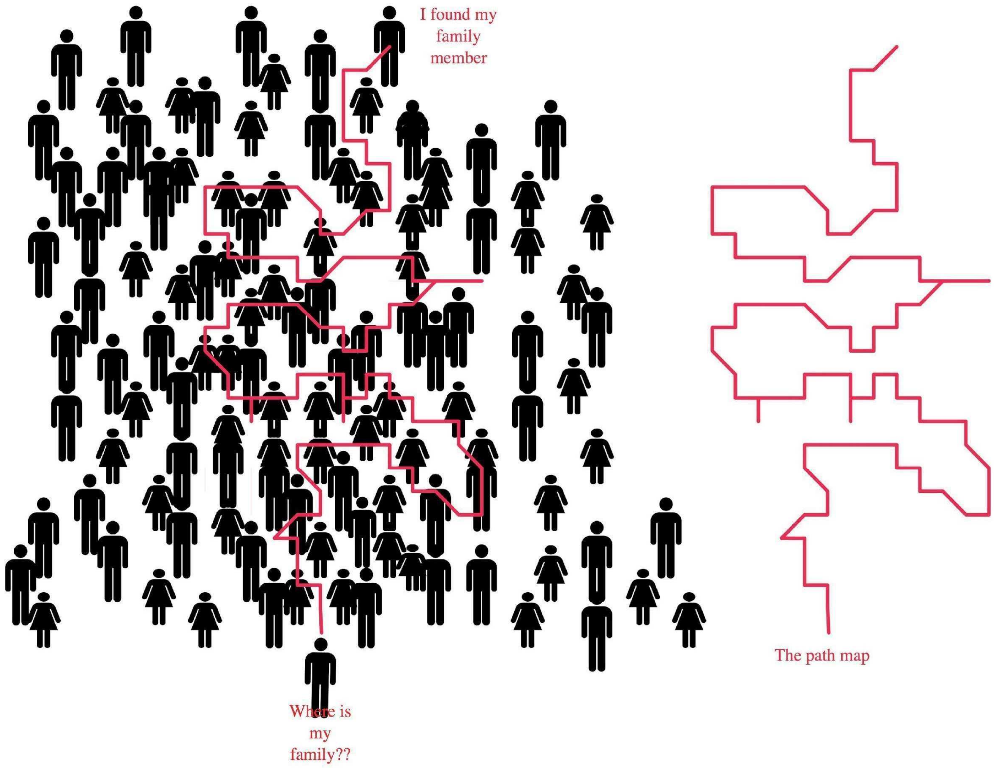


Figure 8.0: A small simulation of crowded area environment map.

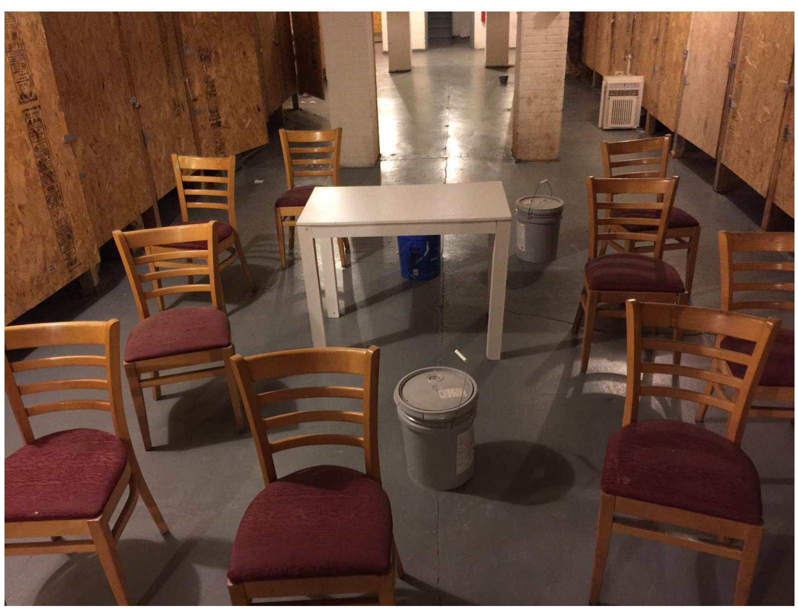


Figure 9.0: The small simulation of crowded Area for recording Moving Randomly Activity

Participants in the study were free to start and stop collecting data as they saw fit, but had to annotate the phone placement in the hand at the start of each activity. This was done using a multiple choice feature in the application. In addition, if something went wrong during the data collection, the person was free to delete experimental data at any time. Throughout the entire data collection phase, the applications sampled the tri-axial accelerometer sensor. At the end of the data collection phase, the participants uploaded all of the experimental data from the devices to our Google Drive account on the cloud. For each sample 0.1 seconds of data was recorded.

5.5 Feature Extraction

The magnitude of each activity was calculated from the raw accelerometer data that was obtained during the data collection process. The calculations were made for each activity on each smartphone. The data was then extracted for further analysis. The ARFF format consists of two sections: a header section and a data section. The header contains a list of attributes "extracted features" and their types along with the name of the relation "Activity Recognition". The data is then arranged as a list of instances.

5.6 Classification Algorithms For Activity Recognition

The classification algorithm is one of the important aspects of the research in Human Activity Recognition (HAR). Any classification algorithm can be used to classify the different movements based on the user inputs from the smartphones, as obtained during the data collection phase [32][40]. In order to decide which algorithm would work best, the different classification techniques were compared on the basis of predictive accuracy, speed, robustness, scalability, and interpretability criteria [14].

In the field of human activity recognition, there are many popular and useful algorithms to choose from when it comes to classification and other data analysis. Naïve Bayes, Multilayer Perceptron, Sequential Minimal Observation (SMO), Decision Tree (J48, Random Forest, Reduced Error Pruning), LogitBoost, and Bayes Network-Nearest-Neighbor (NNN) are all examples of algorithms used for HAR [22].

We chose to focus our research project on the decision tree algorithm. Classifiers J48 were prepared. The algorithm can be executed right on the Android smartphone, which works very well for our research and experiment [33]. It can also be done on an external platform, such as a workstation. We decided to use the decision tree algorithm as our method of classification algorithm because of its compatibility with the processing platform - the smartphone is able to execute the algorithm without any external or additional platform.

5.6.1 Decision tree classifier

A decision tree chart begins at the internal node. This node represents a test. The decision tree chart is then comprised of a series of nodes which resemble the shape of a tree. The nodes are connected linearly, similar to the way one would construct a flowchart [33]. The internal node represents a test, and then each outcome of that test is represented by a branch drawn off of the main node. The leaf nodes are then drawn in with a circle outline. Each leaf node represents class or classes of distribution [14][32][33]. Further internal nodes, again representing tests, can be added to the chart.

These additional nodes are outlined with rectangles. The oval at the top of the chart is called the root node [32][33].

In human activity recognition, as well as other types of research, decision trees have long been used as a method of data mining. They are very useful in pattern recognition and information extraction because a decision tree can include a huge and complex amount of data [14]. They provide a way of seeing useful patterns in the data that a person would have great difficulty discovering without the use of a decision tree. In this way, knowledge can be extracted from a huge amount of raw data. The decision tree follows a classification function, and is therefore sometimes called a classification tree [32]. The independent variables of the classification function are the “input” and the dependent variables of the function are the “output,” found at the conclusion of the decision tree [33]. The user can also add additional information to the chart, such as chance results, utilities, and costs. Figure 14 shows an example of a decision tree and our project expectation tree.

5.6.1.1 J48 Algorithm

J48 is an algorithm developed by Ross Quinlan [32]. It is a decision tree based learning approach based on ID3 (Iterative Dichotomiser 3) [7]. The root node is split into two parts repeatedly until a leaf node - also known at the target node - occurs using a divide and conquer (D&C) algorithm [41].

A J48 decision tree is used to predict a target variable of a new dataset. For example, a user can apply the J48 decision tree to analyze a large dataset such as a long list of independent variables (predictors) and a long list of dependent variables (targets) to predict the target new variable [33]. The weka project team developed the algorithm ID3 (Iterative Dichotomiser 3) algorithm, which is the basis for the J48 decision tree. ID3 searches through a list of possible decision trees and organizes the search from simplest to most complex [36]. We used J48 algorithm through weka because the output source code is generated in Java. We can easily use Java and implement it in our system.

5.6.2 Cross-Validation Test

A cross-validation (CV) test can be used to validate the predicted model. The CV method divides the experimental data into many partitions, usually called folds [8]. The means of evaluating the classifier is then based on and the accuracy of one phase after having learned from another phase. The folding process can then be done again until all of the partitions have been used in the evaluation process [138]. A few of the most popular types of cross-validation tests include the 10-fold, n-fold, and bootstrap. Each of these types will condense the results into a single estimation [8].

5.6.3 WEKA

Weka Toolkit [236] is freely available and allows users to access multiple existing algorithms in a machine learning toolbox. Among the machine learning algorithms available is J48, one of the decision tree algorithms C4.5 [7]. Many researchers use weka in their projects on activity recognition because it is free, easy to use, and provides a variety of options. J48, described above, is commonly used for activity recognition research as a classification model and is the algorithm used in this research.

5.6.4 Confusion Matrix

In order to describe the performance of a classification model, a confusion matrix may be used. A confusion matrix can only be used on a set of test data for which the true values are known [42]. An example is shown In Table 1.0. This matrix is for a binary classifier. Instances that are correctly classified are shown in the right diagonal elements TP (true positive) and TN (true negative). Instances that are incorrectly classified are shown at FP (false positive) and FN (false negative) [32]. The equations listed below can then be used to calculate the correctly and incorrectly classified instances. All of the information from the standard terms above - Recall, Precision, F-Measure, Accuracy, and total number of instances - is used in the calculations.

Table 1.0: An example confusion matrix for a binary classifier (Yes, No).

	Predicted Yes	Predicted NO
Actual Yes	TP	FN
Actual No	FP	TN

5.6.4.1 Recall

In order to determine recall, simply find the ratio of the number of relevant records retrieved compared to the total number of relevant records in the dataset [37:442]. The relationship between Precision and Recall can be expressed in ratios, see Figure 9.0.

$$Recall = \frac{TP}{TP + FN} \tag{5.4}$$

5.6.4.2 Precision

Precision can be determined in a similar fashion [43]. Simply find the ratio of the number of relevant records retrieved compared to the total number of records retrieved, whether irrelevant or relevant. Precision can be expressed as a percentage [37:442]. The relationship between Precision and Recall can be expressed in ratios, see Figure 9.0 [43].

$$Precisi\square n = \frac{TP}{TP + FP} \tag{5.5}$$

5.6.4.3 F-Measure

F measure (FM) is sometimes called the harmonic mean of precision and recall. It is a combination of the two ratios. a combination of recall and precision [32][43].

$$F_{Measure} = \frac{2 * Recall * Precision}{Recall + Precision} \tag{5.6}$$

5.6.4.4 Accuracy

Accuracy can be calculated by comparing correctly classified instances to total number of instances [32][43]. It is also expressed as a ratio.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + TF} \tag{5.7}$$

5.6.4.5 Other Equations

- $Correct\ Instances = TP + TN$ (5.1)
- $Incorrect\ Instances = FP + FN$ (5.2)
- $Total\ Instances = Correct\ Instances + Incorrect\ Instances$ (5.3)

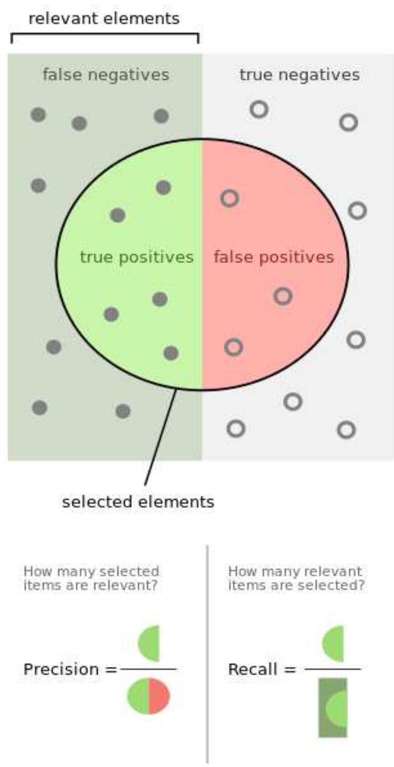


Figure 10: The Relationship between Precision and Recall. [19]

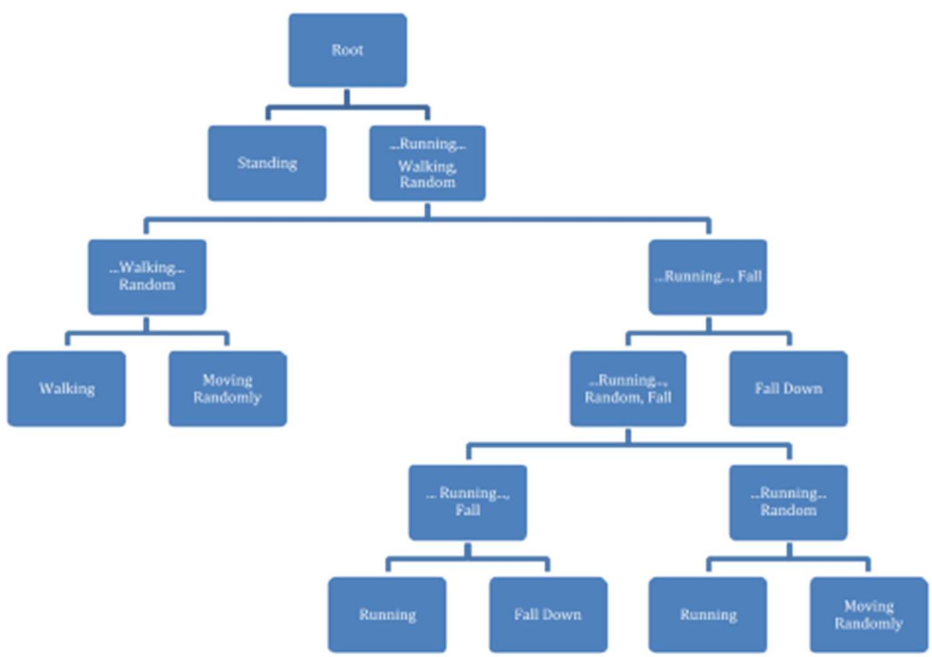


Figure 11: An example of a decision tree classifier and our project expectation tree

CHAPTER 6: EXPERIMENTAL WORK AND ANALYSIS

6.1 Experimental Work and Analysis

One .arff file contains our dataset and the combined feature-extracted data from 8 subjects and 6,339 instances. The file implemented 10-fold cross validation on training data using the Weka toolkit [36]. *K*-fold validation used *k*-1 folds for training and the remaining one for testing. In other words, the dataset was divided into 10 separate sections. The classifier was then tested 10 times. In each test, a different section was chosen as the test set. Finally, the other nine sections were used as the training set. When they were evaluated compared to different classifiers using the same activity recognition data, J48 classifiers obtained a higher accuracy score.

Table 2.0 shows the weka-generated confusion matrix for the J48 classifier. We are able to see many details from the confusion matrix. The total number of instances was calculated by (5.3), and is 6,339 instances. In Figure 10, we can determine how many instances for each activity were recorded. The number of correctly classified instances is 5,808 instances which was calculated by (5.1), while the number of incorrectly classified instances is 531 instances which was calculated by (5.2). From these results, the accuracy rate of estimation activities is 91.6233 % which was calculated by (5.7), while the percentage wrong in the accuracy rate is 8.3767 % (Figure 11).

Table 2: Confusion Matrix of the classification results

Classification	Standing	Walking	Running	Fall-Down	Moving Randomly
Standing	1439	0	0	0	1
Walking	0	1470	2	1	131
Running/ Jogging	0	1	984	8	106
Falling Down	0	0	0	722	0
Moving Randomly	0	150	121	19	1193

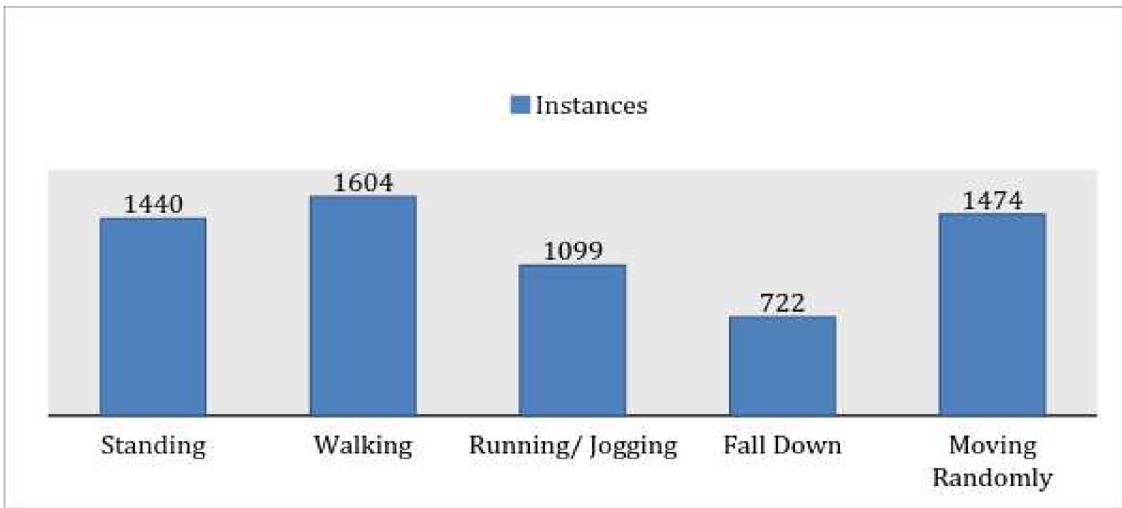


Figure 12: A number of instances for each activity were recording.

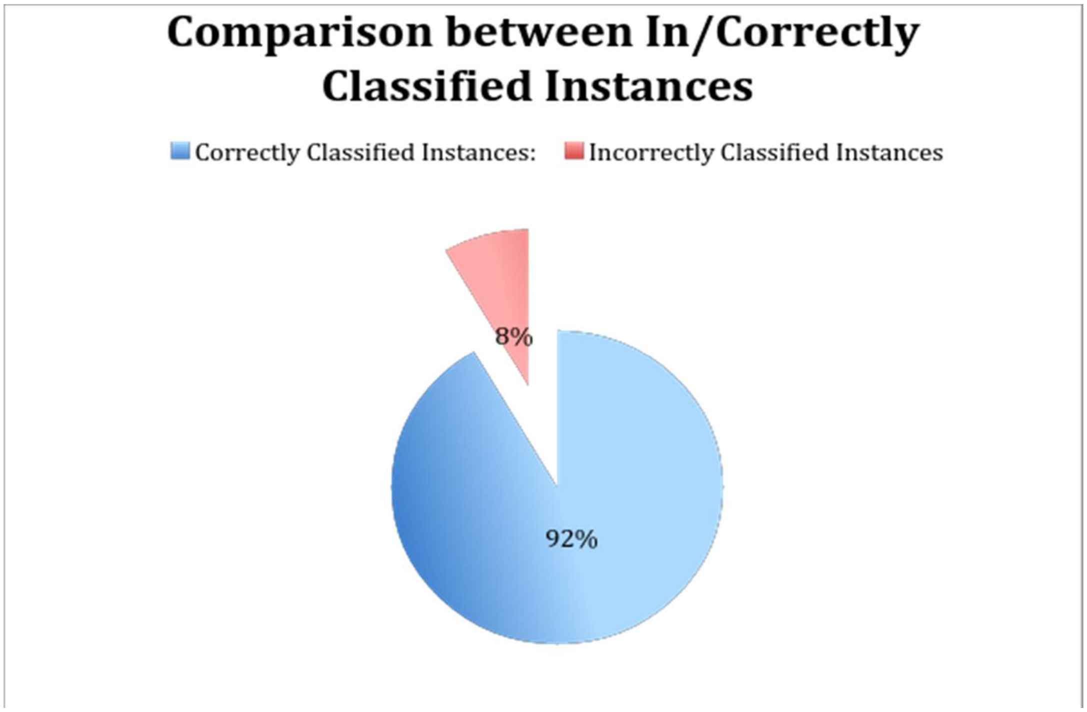


Figure 13: Comparison between Correctly and Incorrectly Classified Instances.

The matrix in Table 3 also includes precision, recall, and F-measure values. All these terms were recorded the same value which is 0.916, and the equations for these terms are (5.5), (5.4) and (5.6) respectively. Recall gives us the measure of completeness - how good is our quantity of information. Precision gives us the measure of accuracy - how exact or what is the quality of information [40]. To explain in more detail, standing, walking, running/ jogging, and falling down had the highest overall precision values: 1, 0.90, 0.89 and 0.94 respectively. Activity that was somewhat more difficult to recognize, which returned slightly lower precision values, includes the activity of moving randomly with value of 0.83 (Table 3).

Table 3: Prediction Performance Measures

Class	TP Rate	FP Rate	Precision	Recal l	F-Measure
Standing	0.999	0	1	0.999	1
Walking	0.916	0.032	0.907	0.916	0.912
Running/ Jogging	0.895	0.023	0.889	0.895	0.892
Fall Down	1	0.003	0.974	1	0.987
Moving Randomly	0.809	0.049	0.834	0.809	0.821
Avg.	0.916	0.024	0.916	0.916	0.916

6.2 Results Summary

We plotted a bar graph from the results obtained from Weka. We are able to achieve over 83 percent accuracy for recognizing random motion (Figure 12).

We then plotted a line graph of the acceleration from the same results along the x, y, and z axis. Looking at the five graphs, we found the maximal values for each activity. The maximal values differed for each activity and the ranges of fluctuation are also different.

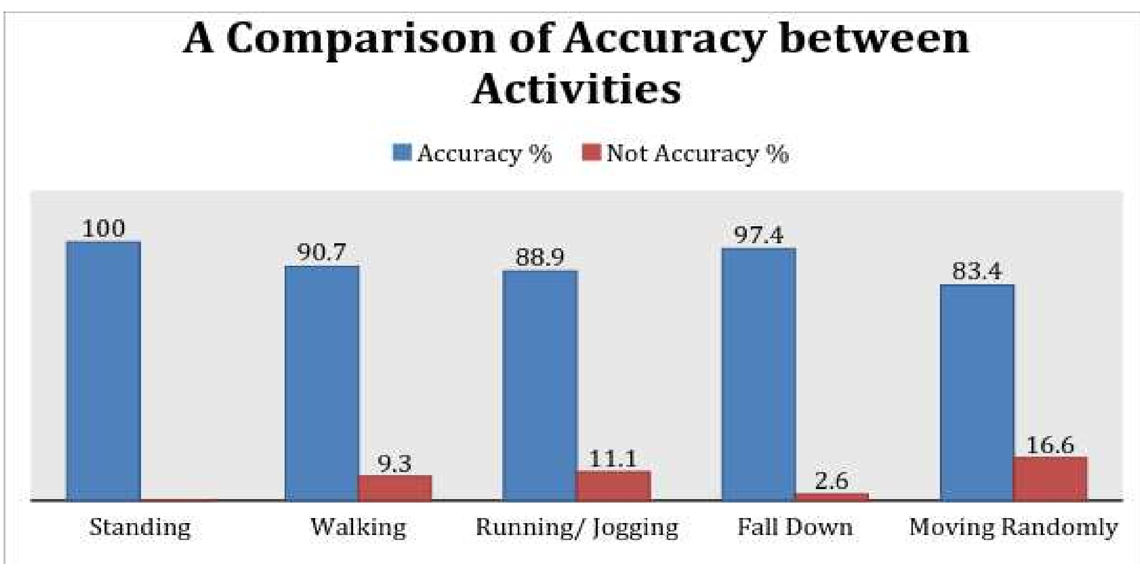
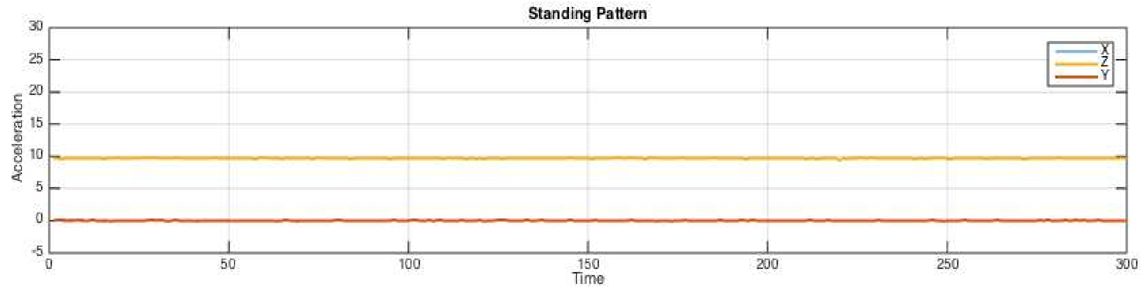
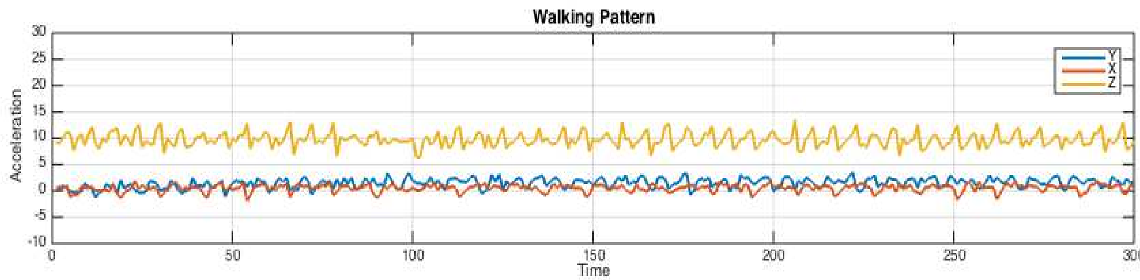


Figure 14: Comparing accuracy across various activities.



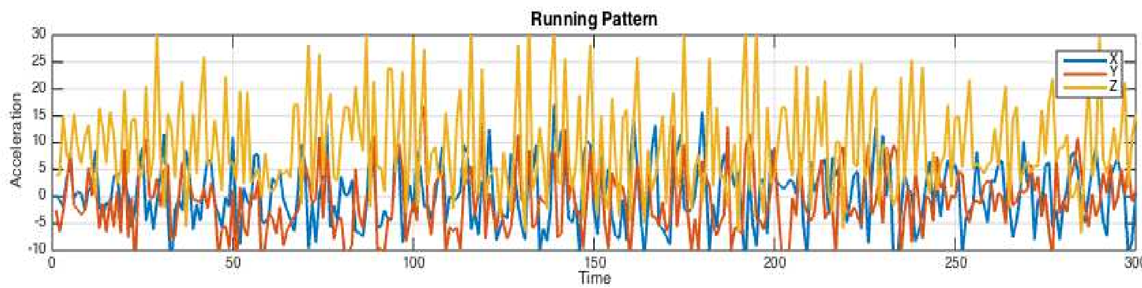
Standing Pattern
X
Z
Y
Acceleration
Time

(a)



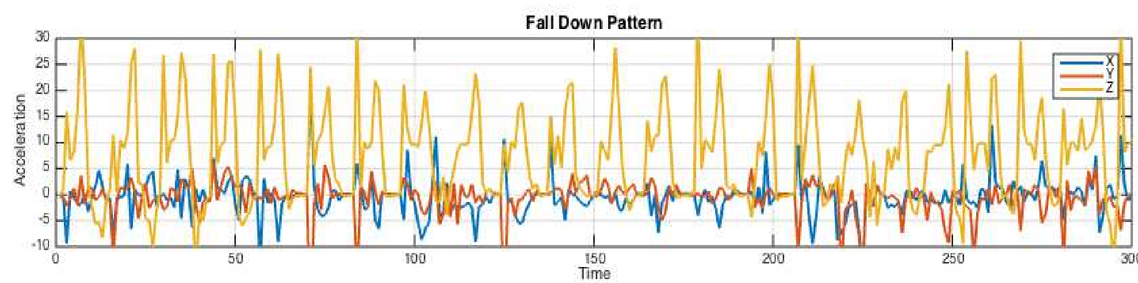
Walking Pattern
Y
X
Z
Acceleration
Time

(b)



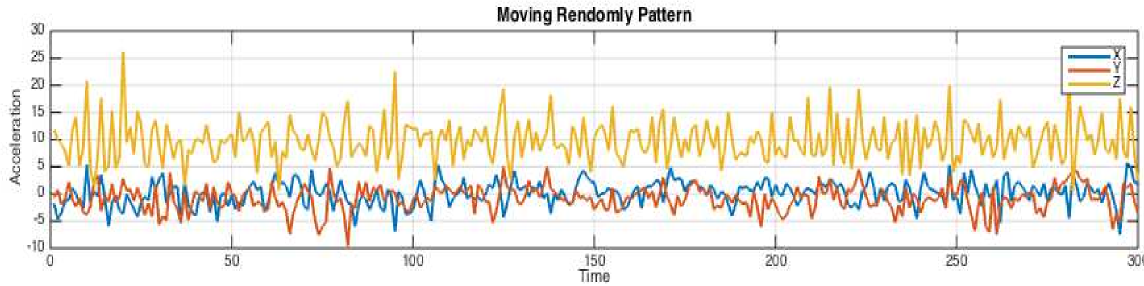
Running Pattern
X
Y
Z
Acceleration
Time

(c)



Fall Down Pattern
X
Y
Z
Acceleration
Time

(d)



(e)

Figure 15. Graphs of acceleration on the x, y, and z axis. Each activity displays a distinct pattern. All five are periodic (a) standing (b) walking (c) running/jogging (d) falling down (e) moving randomly.

CHAPTER 7: IMPLEMENTATION

7.1 Overview

In this chapter, we discuss and present the application prototype which estimates and recognizes the lost person movement patterns: running/ jogging, moving randomly, and falling down. We discuss the implementation of the system and how it can be used on the smartphone.

7.2 Systems Design

The first step was collecting the training data; the second step was analyzing the training data. After completion of data analysis, the next step is implementation of the activity classifier into our application for the Android smartphone.

This system provides a case study on how the movement pattern of a lost person can be extracted from an application on a smartphone. The system records sensor data gathered from the smartphone's tri-axial accelerometer. Wherever the user brings their phone, the application will be recording and analyzing the data constantly. Further, data can be processed and it can be determined if the person's movement is following a normal or abnormal pattern. If the user's movement pattern is determined to be abnormal, the interpretation is that the user may be lost. In our system, we can recognize and differentiate running/ jogging, fall down, and random motion patterns from the other activities on the premise that these motions simulate the movement of a lost individual. We followed a smartphone-programming tutorial from Dartmouth [38] along with other websites in order to complete this project. Figure 14 shows the use cases of the app and Figure 15 shows main process acts.

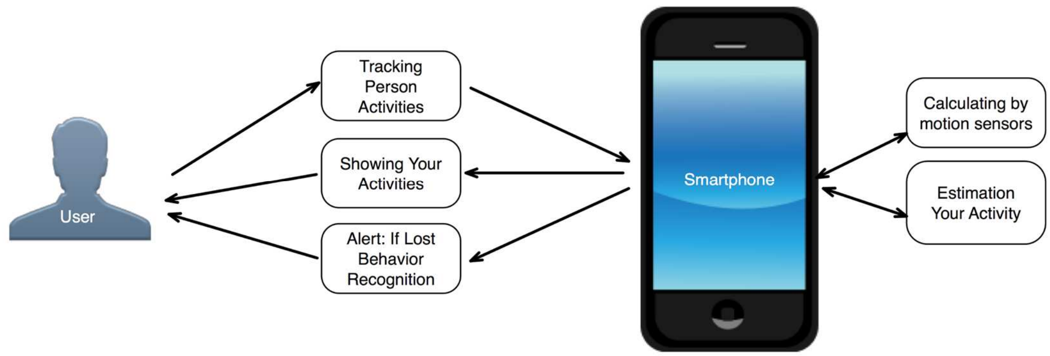


Figure 16. The use cases of the app.

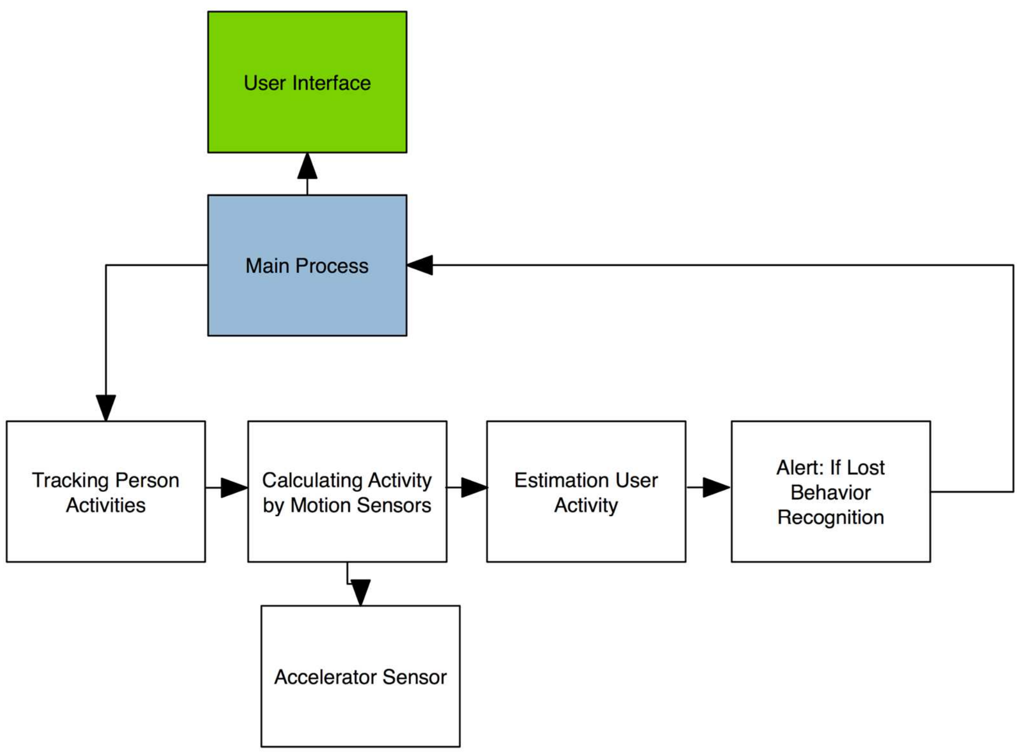
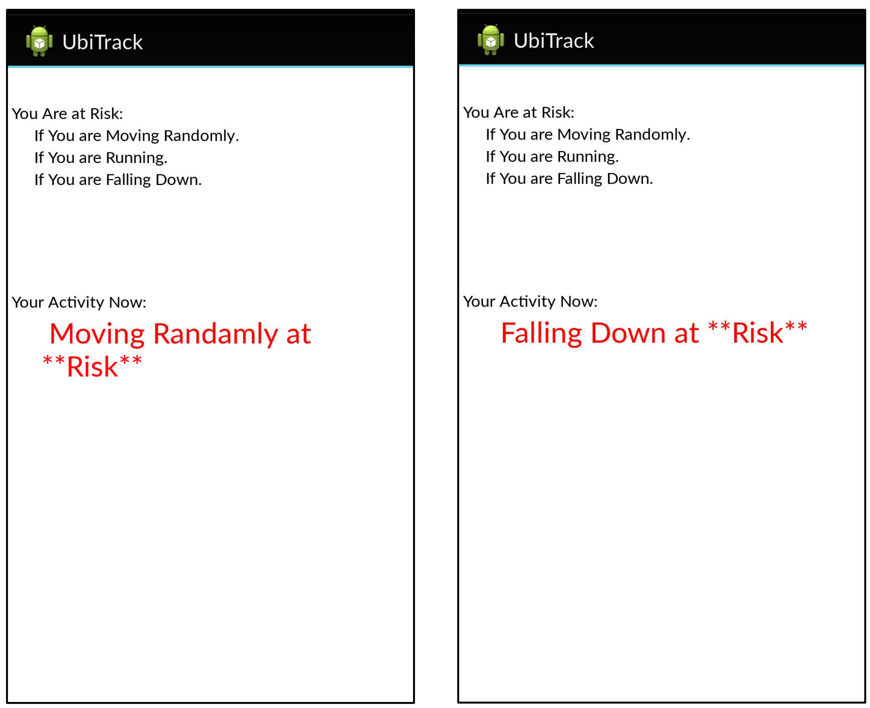


Figure 17: Flow chart. The main process acts as supervisor to the subclasses.

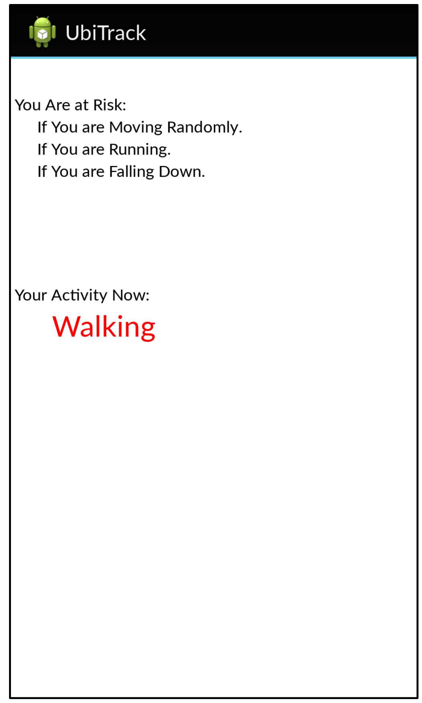
7.3 User Interface

In the demo of our application, we built a system for detecting lost person behavior, and as we can see in Figure 16, we display the five activities that the app can detect from the user's activity (moving randomly, running/ jogging, falling down, walking, and standing). Also, from these five, the app can detect and differentiate any activity that might indicate the person is at risk: moving randomly, running/ jogging, and falling down.

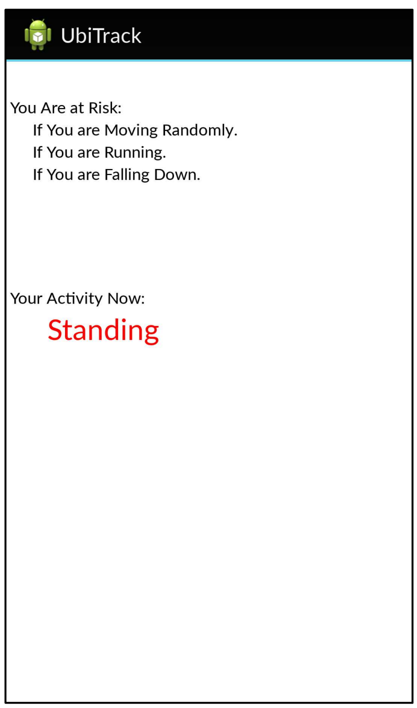


(a) (b)

(c)



(d)



(e)

Figure 18: (a, b, c, d, e) Demo interface of the Ubitrack app.

CHAPTER 8: DISCUSSION

8.1 Activity Recognition Results

After testing our system on the five different activities, we can now discuss the results. We found that the classification system can accurately differentiate between four of the activities - standing, walking, running, and falling down. This is because they are basic activities with one basic pattern of motion that either occurs one time, or repeats in a steady pattern. Moving randomly was a motion that the classifier could not as accurately distinguish from the other four activities. We expected that this would be the most difficult activity to track because it involves many possible motions occurring in a random order, not repetitive motion such as walking or running or a single motion such as falling down. Because of the randomness, this final activity is inherently difficult to detect accurately from the other four.

8.2 Moving Randomly Activity

This is unfortunate because, as we learned in chapter two, the typical behavior of any lost person usually involves moving around in many random directions, not on a clear path [5]. The question that forms the basis of our research is: how does a person typically move when they become lost? Or, in other words, what type of activity or motion would indicate a lost person? We can answer this question based on our study of lost person behavior in Chapter two. “Fear stimulates a heightened concern for self-preservation, mobilizing the body for flight through the secretion of adrenalin and increased blood supply to the legs. It’s no wonder, therefore, that the lost person’s impulse is to move rather than stay put" [5:11]. It is very rare for a person who is lost to remain in one place. Therefore, we are clearly looking for a lot of movement. The person in this situation will walk, run, or jog while moving left, right, forward, and backward in attempt to see around or between the people of the crowd [5]. Because we are specifically studying crowded areas, the person would be walking randomly - left, right, diagonal, etc. - because there are not enough spaces between people to walk in a straight line. It is not the same as walking straight down a street or sidewalk, it is specifically walking through a very dense crowd, which creates a unique pattern of movement which we are calling "moving randomly." Moreover, if the person sees any space in any direction which let him/her go forward to get better view, he/she may suddenly run because in this moment the person thinks that the space will soon be closed by the volume of the crowd [5][20]. Therefore, we are not only looking for random movement in terms of directionality, but also in terms of speed and acceleration/deceleration.

The movements of running/jogging and walking are both present in the movement of "moving randomly." Therefore, the classification of walking or running/ jogging will be detected, as it is appeared in the confusion matrix Table 2. It is difficult to distinguish moving randomly from these other activities with great accuracy. In Table 2, under the moving randomly classification, the total of confusion instances was 290 from 1474 instances; 150 instances were suspected as walking activity, 121 instances as running activity, and 19 instances as fall down.

To summarize, the 83 % accuracy rating is not bad for recognizing and differentiating random motion patterns from the other activities, and it might be increased in accuracy by using different solutions as described in the future work section. We will discuss this issue and the possible solutions that could be implemented in future work.

CHAPTER 9: CONCLUSION AND FUTURE WORK

9.1 Summary of Findings

In our project, we were able to obtain up to 92% recognition accuracy on lost person behavior. We have created an Ubitrack application for an Android smartphone, with which we can estimate the activity of lost person behavior in large crowds. We tested the application in the real time and the Ubitrack application could quickly recognize trials of all five activities, as we can see in Figure 16. We found that four of the activities (standing, walking, running/jogging, and falling down) obtained a high level of accuracy of detection using the application. The fifth activity, moving randomly, obtained an accuracy rating of 83% accuracy, which is not bad considering that it is a difficult movement to track using only an accelerometer.

9.2 Broader Impacts

Our findings can of course be useful in the future development of our application. In the short term, this research will be further developed to perfect our application that can contribute to the solution of crowd management at Hajj. The application will be tested in a live situation this summer when we travel to Mecca. It can serve as an effective way to indicate a lost person in the crowd and alert when a person becomes lost.

In the long term, this research could be used in a variety of other applications. It could be extended not only to detecting a lost person at Hajj, but in any crowded area. Our specific focus is the crowd in Mecca, as that is the goal behind our project. However, the same research could be used by other researchers interested in applying it to other crowded areas. The technology that we are developing could also be linked to other applications for example mapping applications to locate the lost person. Many people may be interested in our findings and may want to build upon our technology in the future or to meet their own objectives.

9.3 Future Work

The Kingdom of Saudi Arabia is committed to the Ubitrack project. It is a large project, and ongoing, with continued funding from the Kingdom [1]. The goal is to develop a better system for tracking pilgrims during the Hajj. This research is taking place through the Ubicomp Lab at Marquette University. This thesis project is one aspect of the cummulative Ubitrack project [1].

There are several points of improvement which we could make to our project:

1. In the future, we are going to incorporate more sensors such as GPS, gyroscopic sensors, and cameras in order to increase the accuracy of an activity recognition.

2. We can improve an alert system in our project. For example, if the user's movement pattern is determined to be abnormal, the interpretation is that the user may be lost, and the system will transmit a signal that triggers an alarm and starts a timer. If the user does not manually turn off the alarm within a certain time period, the system automatically calls contacts stored in the emergency contact list of the phone, according to priority.

3. We can add the goal of obtaining both outdoor and indoor recognition. This can be obtained by using inertial sensor data and Received Signal Strength Indicator (RSSI) on the wireless device.

4. In Hajj systems, there is a group manager who is responsible for caring for every member of the group during Hajj time, so we have some ideas which can improve our system, specific to this situation. See Figure 17.

a. We can record and track activities of all members in the group by using GPS, accelerometer, gyroscopic sensors, and other sensors. The location of each group member could then be shown on a map. All these data will be stored on the cloud for future access and analysis.

b. The group manager can monitor all members on the map from the office, and the alert system will be activated when any member is at risk.

c. If any person is at risk, it will be easy for the manager to locate him/ her and provide help.

d. Also, if the group manager suspects any person of being at risk, he/she can compare the activity recorder with any other member in the group. After the comparison, they will make sure 100% if this person at risk or not.

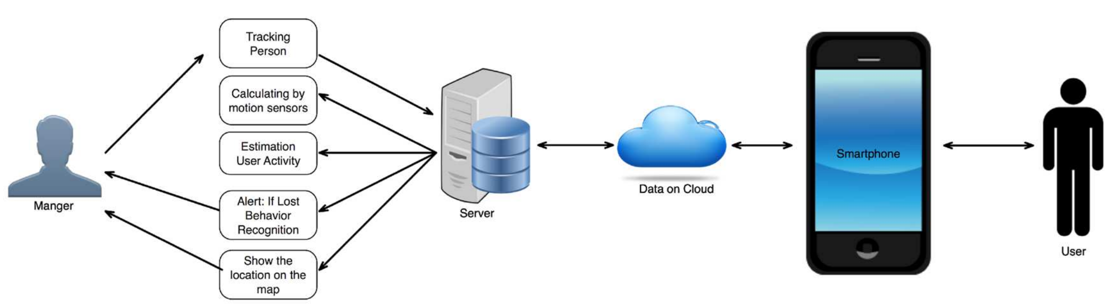


Figure 19. The use case of an improvement our system

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Appendix A

Glossary of terms

Term	Definition
HAR	Human Activity Recognition. This term is used to describe technology that is able to detect human motions.
ARFF	Attribute-Relation File Format. The file is an ASCII text file that describes a list of instances that share a set of attributes.
CSV	Comma Separated Value. This file allows the user to collect data from any table. Data can then be used in another table-oriented application, such as a relational database application. CSV files can be read by Microsoft Excel.
J48	Decision tree J48 is the implementation of algorithm ID3 (Iterative Dichotomiser 3) developed by the WEKA project team. It can be used to predict the target variable of a dataset.
Weka	Weka is a collection of machine learning algorithms for data mining tasks, developed by University of Waikato in New Zealand. Weka is open source software issued under the GNU General Public License.
Cross-Validation (CV)	A technique used to assess how the results of any statistical analysis will generalize to an independent data set. A technique used to estimate the performance of a predictive model.