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Abstract:

As smartphones become more popular, applications are being developed with new and innovative ways to solve problems 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. We use this type of motion sensing technology, specifically, using data collected from the accelerometer sensor. The purpose of this study is to study and estimate the person who may become lost in a crowded area. The application is capable of estimating the movements of people in a crowded area, and 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. In this paper, we review related literature and research that has given us the basis for our own research. 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 evaluate and describe the creation of the application, all of its components, and the testing process.

Author Keywords

- Human Activity Recognition (HAR), Lost Person Behavior and Psychology, Inertial Tracking, Mobile Computing, Ubiquitous Computing, Hajj Smartphones

SECTION I. Introduction

Imagine a person who becomes lost in crowded areas, such as on the Hajj pilgrimage among upwards of two 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 every year [2]. This is an important spiritual ritual for people who follow Islam. 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 that needs to be addressed is that people become lost in the crowd. Ground personnel are overworked already, and it is costly to continuously hire more personnel to track and find missing pilgrims. Therefore, we are looking for a more effective approach to this issue.

Sensors have been used in a variety of ways to detect human activity [4] [6] [7] for some time now. In recent years, phrenology has become more advanced, especially in the use of smartphone applications. Human activity monitoring technology can be applied to a variety of fields and can also be used for the average consumer product. However, it is presently of most use in the areas of healthcare and assisted living [6] [7]. 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 [8]. Millions of people carry a smartphone on a regular basis, so it makes sense to further develop sensor technology for a smartphone application [6].

Human activity recognition is the motivation behind all these advancements in technology. Applications that can detect human movement and location take a raw sensor reading and can then predict human motion and activity [10]. 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 other smartphone applications as well. 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]. Also, applications can be created to locate people who become lost [2]. Due to the low cost of development, smartphone applications have become the leading technology used for human motion and activity recognition [8].

Our solution to the issue of studying and identify lost people in crowded areas is a smartphone application. The application can track a person's movements and activities right on his/her smartphone and display an alert on the screen which might be useful to add a feature sending SOS (Save Our Souls) if the person is displaying unusual behavior, specifically behavior that is indicative of a lost person.

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, and moving randomly without a specific direction and also speed [5].

The goal is to create a system 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

The rest of the paper is organized as follows. Section 2 describes the main motivations for our system. Section 3 shows the background of lost person behavior and psychology in crowded areas. Section 4 discusses existing and related works. Section 5 presents the system development. In Section 6 concludes with a discussion of our results.

SECTION II. Motivation

To further explore our motivation, we offer the following scenarios.

A. 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 Makkah during the Hajj when millions of pilgrims visit at the same time. During the time of pilgrimage, there can be about 4 million people in an area that is only 460 square miles [2].

B. 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.

All these problems continue to arise ever 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 we propose 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.

SECTION III. Background

A. 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 is wrong, such as a possible accident.

It may seem logical to travel in one direction, but most people, when lost, move around in a random pattern [5]. Some people will attempt to follow a trail or a familiar route, but research indicates that 62% of people will leave the trail [13]. "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] [14]. 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 [13]. "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 can 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]. 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 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 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, that would indicate not only that the person is lost, but also that the person may be in some danger. 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] [14]. "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.

B. 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 [13]. Children, age 7–12, are 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. 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 [14].

SECTION IV. Related Works

A. Sensors for Detecting Human Activity

Our paper 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 [11]. Casale et al. used a wearable device to obtain 94% accuracy in human activity recognition based on accelerometer data [11]. Nishkam and Nikhil used a triaxial accelerometer to track human activity and focused on differentiating between eight separate activities or movements [15]. They found that certain activities had a high accuracy of recognition, such as standing versus running. Certain activities have a lower rate of accuracy - they were difficult to distinguish - such as running up the stairs versus running down the stairs [15]. All 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 HAR. Accelerometers and microphones were used in a recognition system developed by Lester et al. [16]. 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 [17]. Casale et. al. studied movement pattern recognition from accelerometer data, also using a wearable, external device [11].

Many projects are like 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 [13]. 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.

B. Lost Person Behavior and Psychology in Crowded Areas

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 [14]. 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 [5]. 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].

Much research exists concerning search and rescue of lost persons. Hill [5] presents a guide for locating lost people - a search and rescue guide, which focuses on searching in urban areas, as opposed to a general search. This research [5] 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 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 system will combine all 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.

C. Algorithm

Several related works [6] [12] 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 [31]. 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 [20]. Also, the output source code generated from J48 is in Java, which works well for our purposes [20].

There are several data mining methods to choose from. Bhargava et. al. [7] explain data mining and Weka, which stands for Waikato environment for knowledge analysis. Weka is freely available online and was developed by the University of Waikato in New Zealand [10] [4]. This system allows users to freely access machine learning algorithms and state of the art data mining systems [4]. 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, etc. [14]

J48 is a specific decision tree algorithm that was developed by Ross Quinlan [20]. 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 [20]. For our study, we chose to streamline the application by executing the algorithm right on the Android smartphone.

SECTION V. Development of the System

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 from the other activities on the premise that these specific motions simulate the typical movements of a person who has become lost. 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.

Figure 1 Human activity recognition

A. Data Collection Procedure

The primary goal here was to analyze the accelerometer data from multiple motor activities such as standing, running, walking, jogging and moving randomly. After the development of the application for Android, the next phase of the study involved collecting data with the use of the application. Five devices, all of which were operated by Android, were used to collect data throughout the experiment during the day. Ten members of Ubicomp Lab at Marquette University were used to collect the experiment data. The subjects ranged in age from 24 to 36 years old. All five devices were held horizontally in the palm of each subject's hand during the experiment. Five types of activity were recorded with experimental data including: standing, walking, running/jogging, falling, and moving randomly.

The basic assumption behind the experiment was very important. This assumption was that in crowded areas, to collect moving randomly and waking data, we were using our application for collecting these activities after the basketball match end which was crowded event. The subjects were walking and moving together. Also, the other activities we were collecting in our lab. You will see that 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.

B. 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" such as "Waking, Running, Falling...etc." and their types along with the name of the relation "Activity Recognition". The magnitude of the acceleration of each of the vectors can be calculated using the formula (1): for a vector i, magnitude of acceleration magi. [11] [18].

$$magi = \sqrt{x^2 + y^2 + z^2}$$

C. 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 [19]. 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 [9].

We used the decision tree algorithm in our research project. Classifiers J48 were prepared. The algorithm can be executed right on the Android smartphone, which works very well for our research and experiment [20]. 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.

SECTION VI. Evaluation

A. Experimental Work and Analysis

The data file contains our dataset and the combined feature-extracted data from ten subjects and 6,339 instances. The file implemented 10-fold cross validation on training data using the Weka toolkit [10]. 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 I shows the Weka-generated confusion matrix for the J48 classifier. We can see many details from the confusion matrix. The total number of instances is 6,339 instances. Also, we can determine how many instances for each activity were recorded. The number of correctly classified instances is 5,808 instances, while the number of incorrectly classified instances is 531 instances. From these results, the accuracy rate of estimation activities is 91.6233%, while the percentage wrong in the accuracy rate is 8.3767% (Figure 2).

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

Classification	Standing	Walking	Running	Fall-Down	Moving Randomly
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Falling Down	0	0	0	722	0
Moving Randomly	0	150	121	19	1193

**Table I:** Confusion matrix of the classification results

B. Results Summary

We plotted a bar graph from the results obtained from Weka. We were able to achieve over 83 percent accuracy for recognizing random motion which is one of the main important activity for lost person behavior (Figure 2).
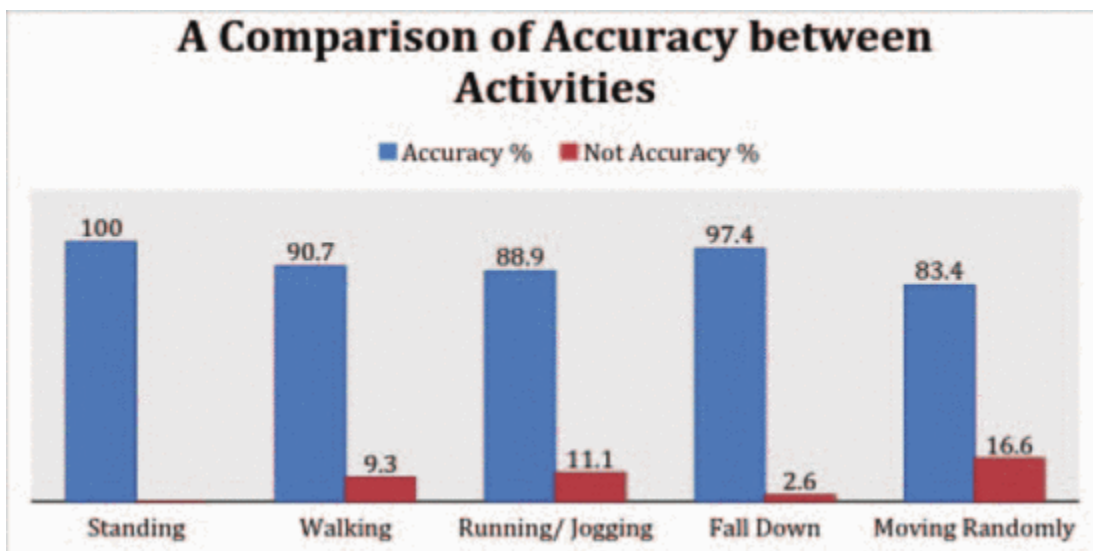
Figure 2: Comparing accuracy across various activities.

C. System Design

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, and random motion patterns from the other activities on the premise that these motions simulate the movement of a lost individual. Figure 3 shows main process acts.
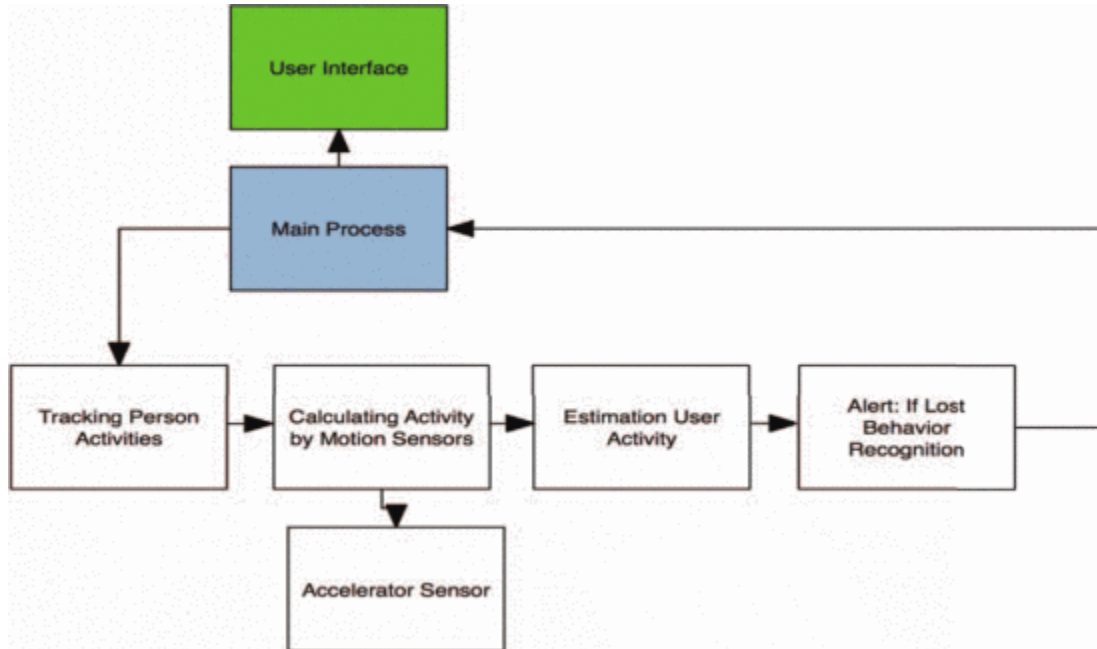
Figure 3: Flow chart. The main process acts as supervisor to the subclasses.

D. User Interface
In the demo of our application, we built a system for detecting lost person behavior, and as shown in Figure 4, we display the four activities that the app can detect from the user's activity (moving randomly, running/jogging, falling, walking, and standing). Also, from these five activities, the app can detect and differentiate any activity that might indicate the person is at risk: moving randomly, running/jogging, and falling.
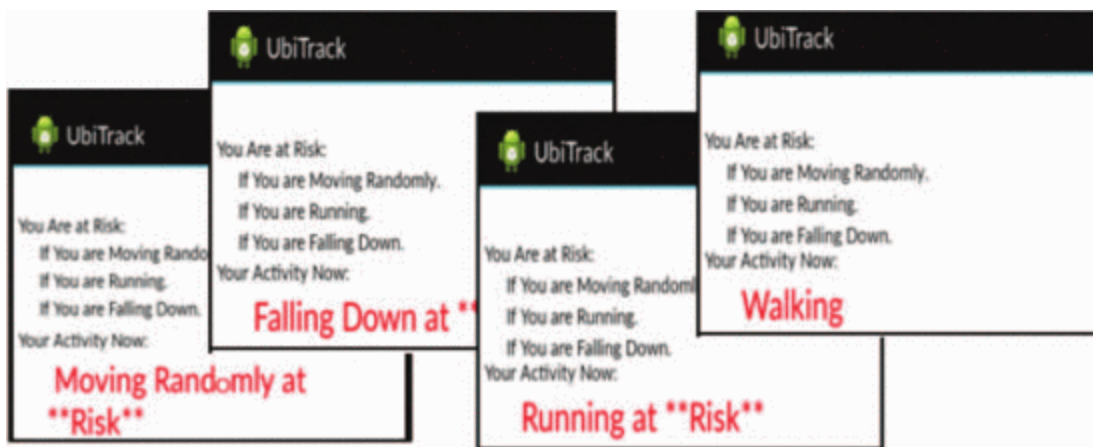
Figure 4: Demo interface of the ubitrack app.

SECTION VII. Conclusion

In our system, we were able to obtain up to 92% recognition accuracy on lost person behavior. We created 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 real time and the Ubitrack application could quickly recognize trials of all five activities, as shown in Figure 4. We found that four of the activities (standing, walking, running/jogging, and falling) 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.

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. 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. Due to the randomness involved in this activity, it is inherently difficult to accurately detect these activities versus the other four activities. In the future, we aim to incorporate more sensors and technologies such as GPS, gyroscopic sensors, cameras, and Received Signal Strength Indicator (RSSI) to increase the accuracy of an activity recognition.

References

1. [online] Available: http://ubicomp.mscs.mu.edu.
2. A. Muaremi, J. Seiter, G. Tröster, A. Bexheti, "Monitor and understand pilgrims: Data collection using smartphones and wearable devices", *UbiCom International Workshop on Human Activity Sensing Corpus and Its Application (HASCA)*, 2013.
3. *Android Open Source Project. (2017). Sensors overview*, [online] Available: http://developer.android.com/guide/topics/sensors/sensors_overview.html.
4. M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, I.H. Witten, "The weka data mining software: an update", *ACM SIGKDD explorations newsletter*, vol. 11, no. 1, pp. 10-18, 2009.
5. K.A. Hill, "The psychology of lost" in Lost Person Behavior, Ottawa, Canada:National SAR Secretariat, pp. 116, 1998.

6. A. Bayat, M. Pomplun, D.A. Tran, "A study on human activity recognition using accelerometer data from smartphones", *Proceedings of the MobiSPC-2014 Procedia Comp. Sci.*, vol. 34, pp. 450-457, Nov. 2014.

7. T.S. Korting, "C4. 5 algorithm and Multivariate Decision Trees" in Image Processing Division, National Institute for Space Research--INPE.

8. A. Ghosh, G. Riccardi, "Recognizing human activities from smartphone sensor signals", *Proc. 22nd ACM International Conference on Multimedia*, 2014.

9. J. Han, M. Kamber, Data Mining: Concept and Techniques, Morgan Kaufmann Publishers, 2006.

10. R. Bouckaert, E. Frank, M. Hall, R. Kirkby, P. Reutemann, A. Seewald, D. Scuse, WEKA Manual for Version 3-6-0, The University of Waikato, 2008.

11. P. Casale, O. Pujol, P. Radeva, "Human activity recognition from accelerometer data using a wearable device" in Pattern Recognition and Image Analysis, Springer, pp. 289, 2011.

12. J. Kwapisz, G. Weiss, S. Moore, "Activity recognition using cell phone accelerometers", *ACM SigKDD Explorations Newsletter*, vol. 12, pp. 2-74, 2011.

13. *Little Egypt Search and Rescue (LESAR). (2015). article 3 Lost Person Behavior*, [online] Available: http://www.lesar.org/article3.htm.

14. D. Hourihan, Predicting lost person behavior, Mount Hood, OR:Mountain Rescue U.S., 2005.

15. N. Ravi, D. Nikhil, P. Mysore, M. Littman, "Activity recognition from accelerometer aaaadata", *AAAI*, pp. 5-1541, 2005.

16. J. Lester, T. Choudhury, G. Borriello, "A practical approach to recognizing physical activities" in Pervasive Computing, Springer, 2006.

17. A. Mannini, A. Sabatini, "Machine learning methods for classifying human physical activity from on-body accelerometers", *Sensors*, vol. 10, pp. 2-1154, 2010.

18. M. Shoaib, S. Bosch, O.D. Incel, H. Scholten, P. Havinga, "Fusion of smartphone motion sensors for physical activity recognition", *Sensors J.*, vol. 14, pp. 10146-10176, June 2014.

19. D.L. Gupta, A. Malviya, S. Satyendra, "Performance Analysis of Classification Tree Learning Algorithms", *International Journal of Computer Applications*, vol. 55, no. 6, 2012.

20. N. Bhargava, G. Sharma, R. Bhargava, M. Mathuria, "Decision Tree Analysis on J48 Algorithm for Data Mining", *Proceedings of International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 3, no. 6, June 2013.