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Three Tier Indoor Localization System for Digital Forensics

Dennis L. Owuor, Okuthe P. Kogeda, Johnson I. Agbinya

Abstract**—**Mobile localization has attracted a great deal of attention recently due to the introduction of wireless networks. Although several localization algorithms and systems have been implemented and discussed in the literature, very few researchers have exploited the gap that exists between indoor localization, tracking, external storage of location information and outdoor localization for the purpose of digital forensics during and after a disaster. The contribution of this paper lies in the implementation of a robust system that is capable of locating, tracking mobile device users and store location information for both indoor and partially outdoor the cloud. The system can be used during disaster to track and locate mobile phone users. The developed system is a mobile application built based on Android, Hypertext Preprocessor (PHP), Cascading Style Sheets (CSS), JavaScript and MATLAB for the Android mobile users. Using Waterfall model of software development, we have implemented a three level system that is able to track, locate and store mobile device information in secure database (cloud) on almost a real time basis. The outcome of the study showed that the developed system is efficient with regard to the tracking and locating mobile devices. The system is also flexible, i.e. can be used in any building with fewer adjustments. Finally, the system is accurate for both indoor and outdoor in terms of locating and tracking mobile devices.

Keywords**—**Indoor localization, waterfall, digital forensics, tracking and cloud.

I. Introduction

FROM time immemorial, man has invented many technical means to aid in direction and navigation. Some of the techniques invented are maps, compass, etc. With the advancement of technology, this has led to invention of navigation assistance systems, e.g. automotive navigation system, marine navigation system, surgical navigation system, robotic mapping, etc. The game changer was the invention of Global Positioning System (GPS) which provides location as well as time information at any section of the earth [1]. Though very popular, GPS has one weakness, it cannot provide accurate information about mobile devices in an indoor environment. Due to the weakness, researchers had to come up with better ways for locating mobile devices in buildings. The introduction of Wi-Fi networking and the complex technology with regard to mobile devices such as the introduction of sensors has escalated the field of indoor localization. Researchers have come up with several algorithms to aid in indoor localization, i.e. Time of Arrival (TOA), Angle of Arrival (AOA), Pedestrian Dead Reckoning (PDR), Triangulation, fingerprinting, sensor motions, sensor fusion, etc. With these algorithms different systems have been implemented to aid locating mobile devices in an indoor environment [2], [3]. Fingerprinting is the most commonly used technique when it comes to Received Signal Strength (RSS)based localization, this technique requires calibration, which can be both offline and online. Though very popular, it can be time consuming especially when offline calibration is needed [4].

Researchers lately fuse PDR techniques and Wi-Fi-based indoor localization techniques in-order to attain more accurate results [5]. With these algorithms several researchers have built systems that are very efficient and accurate. In 2009, Han et al. [6] presented a visual analytics system that enables developers of these localization systems to visually gain insight on whether the datasets stored and selected fingerprint features have essential properties that will enable a reliable FR fingerprint-based localization system. In 2011, Pereira et al. [7] developed a functional application for a smartphone indoor/outdoor localization system publicly available for download by the name “download me”. Chan et al. [8] in 2012combined two different Wi-Fi approaches to locate users in an indoor environment. They used fingerprint matching technique to compare Wi-Fi signal strength stored in their database with the received signal strength information received from nearby Access Points (AP). In 2013, Wu et al. [9] proposed a wireless indoor logical localization approach. By exploiting user motions from mobile phones, they successfully removed the site survey process of traditional approaches, while achieving competitive localization accuracy. An indoor localization approach based on off-the-shelf Wi-Fi infrastructure and mobile phones called Wireless Local Loop (WILL) was developed. In 2014, Lisandro et al. proposed a strategy that lies within the so-called Database Correlation Methods (DCM) which they used to locate Mobile Stations (MS) in wireless networks [10]. In 2015, Pei et al. proposed an indoor localization based on the basis of Important Access Points (IAP) [11]. Wi-Fi AP with the highest RSS was denoted as the IAP. At the localization stage, the fingerprints are chosen with the same IAP as the estimated fingerprint from the database. With these and other systems, one area that has not been exploited by many researchers is the capability of tracking, locating and storing this mobile location information for indoor and outdoor environment in a secure manner; that can be accessed quickly during and after disaster

D. L. Owuor is with the Tshwane University of Technology, South Africa (phone: +27 794089586, fax: 086 625 7197, e-mail: dennisluke11@gmail.com).

P. O. Kogeda is with the Tshwane University of Technology, South Africa (phone: +27 (012) 382 9640, fax: +27 (012) 382 0966).

J. I. Agbinya is with La Trobe University, Australia (phone: (+61) 0414 20 9245).

has taken place for the purpose of digital forensics. Based on this gap, we have reviewed the literature and implemented what we call a three tier localization system that tracks, locates mobile devices' location for both indoor and outdoor environments. The location information is sent to the cloud which is accessed via a website. The proposed system is dynamic, and hence, can be used in any building, it is efficient since it provides information pertaining to the mobile device for both indoor and outdoor environments, and it is also faster since it sends data to the server after every 30seconds. Hence, it has the capability of monitoring mobile devices almost on a real time basis. The remainder of this paper is organized as follows. In Section II, we present related works. In Section III, we present methodology. In Section IV, we present Implementation of KNN and RSS Fingerprinting localization algorithm. In Section V, we present system implementation. In Section VI, we present Android Indoor Localization (Client Side/Android App) Implementation and lastly conclude in Section VII.

II. Related Work

In many scenarios of everyday life especially in indoor environment, it is becoming very important to locate objects or persons very fast and accurately. In big companies or malls, for example, staff or mobile devices should be located and tracked all the time, so that in case of fire or any disaster evacuation and tracking is faster. Indoor location and tracking systems are in high demand since global positioning systems like GPS, GLONASS or Galileo do not perform very well in the indoor environment. In the literature of indoor localization, many techniques have been proposed in the past two decades. These indoor localization systems can be classified as range-based and range-free localization systems depending on the algorithms implemented. Range-based localization scheme often uses Received Signal Strength Indicator (RSSI), TOA or Time Difference of Arrival (TDOA) technique to calculate the distance between two nodes and use various approaches such as trilateration, triangulation and multilateration to help in final location estimation. In light of the costs related to complex ranging systems, researchers have sought range-free methods to the localization problem in wireless sensor networks [12]. Thus, range-free methods do not perform distance measurements or bearing measurements; instead, they use other resources such as connectivity maps, proximity information or signal strength fingerprints for indoor localization. Many researchers have come up with different systems based on the algorithms discussed to aid in indoor localization. Some of these include: Yang et al. in 2012 proposed a wireless indoor localization algorithm approach called Locating in Fingerprint Space (LiFS) [13]. In the proposed approach, one needed to do site survey before even fingerprinting was done. During this survey, all the areas of interest were marked and their locations recorded in a database. The process of surveying the site was very costly, since man-power was needed. The authors made use of the sensors on mobile phones and the user movement to construct the radio map of the floor. To determine mobile device location, probability algorithm was used. The system was implemented in two indoor environment and based on their experiment they achieved an accuracy of 0.65 [13].

In 2012, Wu et al. proposed a wireless indoor logical localization approach. By exploiting user motions from mobile phones, they successfully removed the site survey process of traditional approaches, while achieving competitive localization accuracy. An indoor localization approach based on off-the-shelf Wi-Fi infrastructure and mobile phones called WILL was developed. They utilized untapped RF signal features and leverage user motions to construct a radio floor plan that was previously obtained by site survey. WILL was deployed in a real building covering over 1600m^2, and its deployment was easy and rapid since site survey was no longer needed. Under certain Semantics, WILL is able to use human motions to connect previous independent radio frequency signatures. WILL required no prior knowledge of AP locations and it was not necessary for users to participate by labeling measured Received Signal Strength (RSS) with the equivalent locations. Their experiment results showed that WILL achieved a great performance compared to traditional approaches [9].

In 2014, Hongbo et al. proposed techniques for fast acoustic ranging among multiple phones and built a prototype. Their work was motivated by high densities of smartphones in public spaces, so they proposed a peer assisted localization approach to eliminate such large errors. Their system obtained accurate acoustic ranging estimates among peer phones. Based on their ranging estimate, it mapped the location against Wi-Fi signature. Based on their experiment, error reduced up to 80percentile to as small as 2m and 1m, in time no longer than the original Wi-Fi scanning [14].

In 2015, Jiang et al. proposed an indoor localization based on the basis of IAP. They classified Wi-Fi AP as important or less important. AP were classified based on the received signal strength, i.e. those with the highest received signal strength were marked as the IAPs. During localization, the fingerprints were chosen with the IAP as those estimated fingerprint from the database. The degree was calculated based on distance and AP repetition of the fingerprint. The location was detected based on the match with fingerprint database. Based on their experiment, the proposed algorithm achieved high accuracy in an indoor environment [11].

In 2016, Husen et al. proposed what they called a low-cost solution system for indoor location. They used a combination of dead reckoning, Wi-Fi signal strength fingerprinting and an automated procedure for collecting Wi-Fi calibration data. Finally, they used particle filter to eliminate unnecessary noise, and hence the improved accuracy. The uniqueness of their system was on the efficient adaptation to the mobile phone platform. Their system was implemented using multiple participants in two different indoor environments and achieved localization accuracies of 5 meters [15].

These and many other applications have been implemented to aid in indoor localization. However, one area that has not been looked at in-depth is how these indoor localization algorithms can be used to come up with systems that can aid in digital forensics. Therefore, there is need to come up with one robust system that not only locates mobile devices in an indoor environment, but tracks and stores these location information in secure location that can be accessed and used during digital forensics investigation. In this paper, we propose a three-tier indoor localization and partial outdoor localization system. The three major components of our system are the client side (Android app which contains tracking and locating mobile devices), server (cloud) and the server side system (PHP, CSS and Hypertext Markup Language (HTML)) which is accessed via a website. The system can be used during forensics as a basic source of data or information.

III. Methodology

The proposed system has implemented sensor fusion algorithm, Wi-Fi fingerprinting algorithm and K-Nearest Neighbors (KNN) algorithm. The sensor fusion algorithm aids live tracking of the mobile device in an indoor environment, while fingerprinting algorithms and KNN algorithms are used in determining the location of the mobile device in an indoor environment. With sensor fusion, we use the common sensors in a mobile Android device accelerometer, gyroscope and compass in order to determine the orientation, direction and angle of rotation during the movement.

A. Accelerometer

It measures the acceleration in three axes in m/s^2. It outputs the acceleration applied to the device by measuring forces applied to the sensor. The measured acceleration is always influenced by the force of the earth's gravity [16]. This is given by (1):

$$a_d = -g - \sum \frac{F}{m} \qquad (1)$$

(1)

where a_d is the acceleration applied to the device, g the force of gravity, F the force acting on the device and m the mass of the device. The sign $\sum$ represents the sum of the x-, y- and z-axis.

As a result, when the device is in free fall and therefore accelerating towards the ground at 9.81 m/s^2, its output will generate 0 m/s^2 for all three axes. Thus, when the device is put on the table (and obviously not accelerating), the accelerometer output from the x, y and z axis is shown in (2):

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix} \qquad (2)$$

The g is earth's gravity of 9.81 m/s^2. Fig. 1 shows the phone's actual acceleration output for the x, y and z axes when it is stationary on a table.

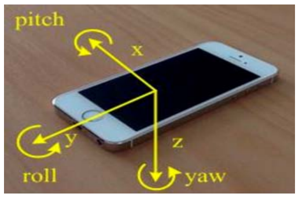

Fig. 1 Stationary Mobile device (x-, y, z-axes) [17]

B. Gyroscope

Its design consists of a freely-rotating disk called a rotor, mounted onto a spinning axis in the centre of a larger and more stable wheel. To detect which way is "down" based on the gravitational pull, the rotor remains static during axis spinning. Fig. 2, shows gyroscope measuring x and y axis on a given angle. Smartphones use gyro sensors to detect the orientation of the device (smartphone). When the smartphone is placed on a flat horizontal surface, it gives a reading of zero. Any slight change on the orientation will be detected by gyro sensor. Smartphones and other electronic devices normally use what is called MEMS (Microelectromechanical systems) machine. In fact, the true origin of a gyroscope is from the law of conservation of angular momentum, so definitely something should move in order for it to have momentum. Modern gyroscopes use this MEMS structure to vibrate at a particular frequency and in the needed direction. The impact of change of orientation is measured from the variation of vibration and usually transmitted out in inter-integrated circuit (I2C) or via serial peripheral interface (SPI) protocols [18], [19].

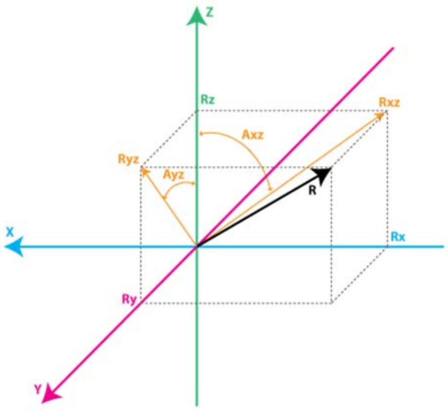

Fig. 2 Gyroscope measuring x and y axis on a given angle [18], [19]

C. Compass Sensor

Compass is a tool that aid in direction detection with respect to the north-south pole of the earth with the aid of magnetism. The same principle was incorporated into smartphones and used to detect the orientation and direction of the phone. An example of a compass in a smartphone is shown in Fig. 3. These three sensors discussed are implemented in our system in order to help in detecting the movement, orientation and change of direction in a process called sensor fusion. Though the research states that sensor fusion is affected by much noise, and hence, can lead to wrong outcome, in our

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application, we use a low pass filter to eliminate the noise.

Fig. 3 Compass Sensor on Smartphones [17]

D.Step Detection Algorithm

The proposed system utilizes step detection algorithms to detect movement in conjunction with the accelerometer and compass. The sensor data are sampled at the fastest possible rate provided by the sensor. These values are low pass-filtered to only include major movements. During implementation, we calculated the direction aligned to the magnetic north of the map a! and adjusted the position with the step size s and grid spacing g as given by (3) and Fig. 4 [20].

$$p_{n+1}(x,y) = p_n\left(x+\sin(a_c+a_m)*s*g, y+\cos(a_c+a_m)*s*g\right) \quad (3)$$

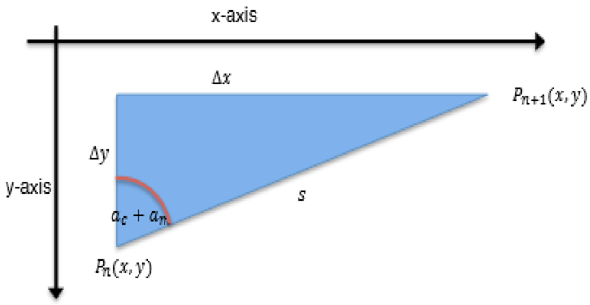

Fig. 4 Step detection algorithm [20]

E. Automatic AP Detector Algorithm

The algorithm used is Local Signal Strength Gradient Algorithm. It is a novel approach that localizes AP using direct information derived from local signal strength variations. The algorithm calculates received signal strength within reach and estimates the direction from which the received signals are coming from. The algorithm consists of two parts, i.e. the calculation of the direction towards which the AP is estimated to be located. This is done by calculating the direction and received signal strength. The final part calculates the point that minimizes the sum-square angular error of all arrows previously calculated. The x and y values of all the surrounding points within a given environment are taken and put in an n*3 matrix, as shown in (4). The last column is filled with ones [21].

$$p = \begin{pmatrix} 1 & 3 & 1 \\ 2 & 2 & 1 \\ 4 & 6 & 1 \end{pmatrix} \quad (4)$$

The average Received Signal for a specific co-ordinate is calculated and stored in 1 by 1 matrix as given by (5):

$$RSSI = \begin{pmatrix} -40.17 \\ -42.20 \\ -41.94 \end{pmatrix} \quad (5)$$

With the aid of least squares method that is majorly used to calculate the best-fitting plane for a set of points in a three-dimension co-ordinate system to get the best-fitting plane C; we divide the two matrices *A* and *RSSI*, as shown in (6):

$$C = A / RSSI \quad (6)$$

For better accuracy, weighting each measuring point by its signal strength improves the accuracy of the algorithm. The weight formula is shown in (7) where w_i is the weight by which each measuring data set is prioritized.

$$w_i = \frac{RSSIP_i}{\sum RSSIP} \quad (7)$$

With the direction of the AP known, the next step is to calculate the AP location automatically. We need to know the angle of the direction and the angle of the point seen from the direction. The angle of direction is calculated as shown in (8) while the angle of point is shown in (9):

$$a_a(k) = a\tan 2\left(a_{ay}(k), a_{ax}(k)\right) \quad (8)$$

$$\left(a_{a(k)p(i)} = a\tan 2\left(p_y(i)\right) - a_{py}(k), p_x(i) - a_{px}(k)\right) \quad (9)$$

Based on the two angles we can now calculate the angle difference or the angular error using the formula shown in (10):

$$\Delta a_{a(k)p(i)} = \left| a_{a(k)} - a_{a(k)p(i)} \right| \quad (10)$$

Once the angular error of all the directions is calculated for a given point $p(i)$, these errors are squared, multiplied with the weight w_i and summed up, as indicated in (11):

$$E\left(p(i)\right) = \sum_{k=1}^{N} \left(\Delta a_{a(k)p(i)}\right)^2 \cdot w_i \quad (11)$$

The AP is likely to be at the point $p(i)$ where the sum-squared angular error is minimum.

F. Localization Algorithms

With the AP detected automatically by the proposed algorithm, the next step is to use an indoor localization algorithm to detect the location of the mobile device. The algorithms to implement indoor localization used are KNN and Fingerprinting localization algorithm to aid in locating mobile device in an indoor environment.

G.K-Nearest Neighbors Algorithm (KNN) and Fingerprinting Algorithms

The K-Nearest Neighbors method is very popular when it comes to fingerprinting algorithms because it is one of the simplest ways to determine the location of a mobile device in a Wi-Fi indoor environment. The idea is to compare the fingerprints in the database (radio map) to the observed measurements and to select K calibration points with the "nearest" RSSI values. The location is estimated using the average of the coordinate's k nearest fingerprints.

$$\hat{x} = \sum_{i=1}^{M} \frac{w_i}{\sum_{j=1}^{M} w_j} p^i \qquad (12)$$

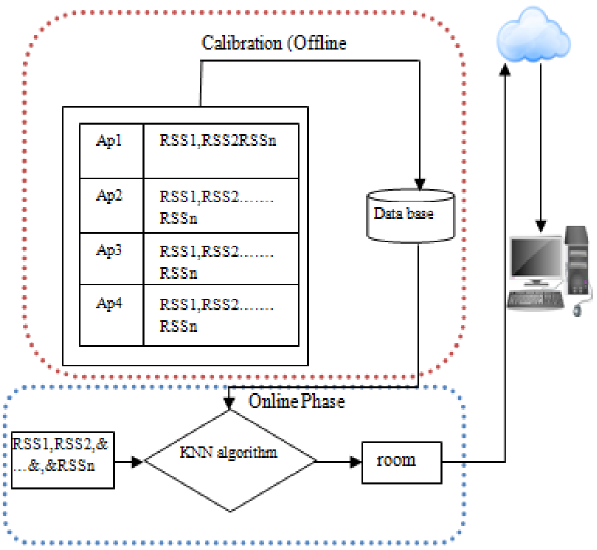

Fig. 5 RSS and KNN algorithms

The fingerprinting localization model consists of two parts: the offline and the online phase. During the offline phase, the database is populated with various RSS from a mobile device from various location coordinates in an indoor environment. Also recorded in the database are the MAC addresses and the AP from which the received signal strength is measured from. During the online phase, the location of the Wi-Fi mobile device is estimated based on the information in the database. Probabilistic or deterministic algorithm is used to aid in determining the coordinates of the mobile device in question. Fig. 5 indicates the design of the proposed fingerprinting algorithm.

IV. Implementation of KNN and RSS Fingerprinting Localization Algorithm

Our experimental testbed is located in our university premises (Tshwane University of Technology), which spans an area of 450 m^2. The experiment was carried out at the Alma DuToit building. The proposed mobile application collected and stored RSS from different APs. For example, Fig. 6 is a graphical representation of RSS data for a specific location in an indoor environment.

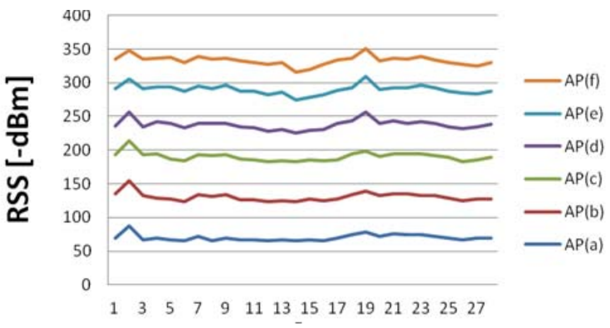

Fig. 6 RSS and KNN algorithms

During calibration, RSS from APs is collected. Then the average of the RSS with regard to APs are calculated and then stored. Fig. 7 below is a graphical representation of the mean values of RSS Stored in the database.

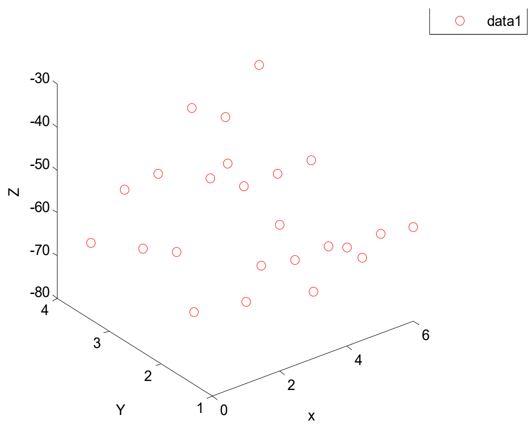

Fig. 7 RSS mean values in dBm

The more one gets close to a specific AP, the higher the RSS with regard to that specific AP. Basically, if you label all your AP one can easily estimate the location of the mobile device just based on the AP. Fig. 8 gives the intensity of RSS at different locations in a building.

The calibrated RSS are stored as shown in Fig. 9 to be used by KNN or any other algorithm to estimate the current location of a mobile device in the specified building.

KNN, which is an old algorithm, but still being classified as one of the top 10 most effective and efficient algorithms in terms of data mining and estimations, is used to aid in estimating the location of a mobile device in an indoor environment.

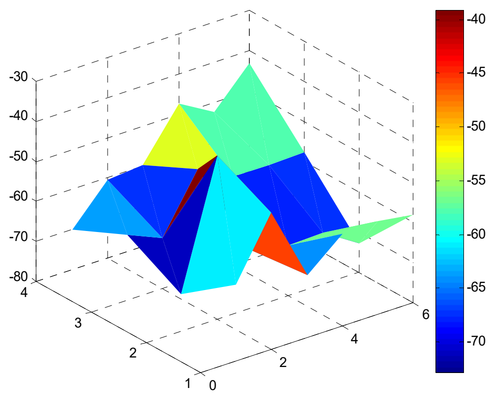

Fig. 8 RSS intensity at different points in the building

Based on the RSS stored in our database, we can test the KNN algorithm. We selected a random mobile location in room 603 at Tshwane University of Technology (Alma DuToit), Location = [-60 -40 -65 -58 -43 -45]dBm. Then based on KNN algorithm, it will return a location, which the RSS is originating from. In our case, we are not specific in terms of the coordinates, but we use the rooms as the location, i.e. bedrooms, sitting rooms, etc. KNN algorithm queries the database and determines which RSS signals are close to the RSS in question.

Based on simulation on Fig. 10, we can deduce that the location in question, which is white circles, is closer to red circles and magenta circles. Therefore, we can conclude that the RSS collected was from a Wi-Fi device in the Alma DuToit, Tshwane University Flat 603 in the sitting room. Fig. 11 is a key that shows the RSS per room.

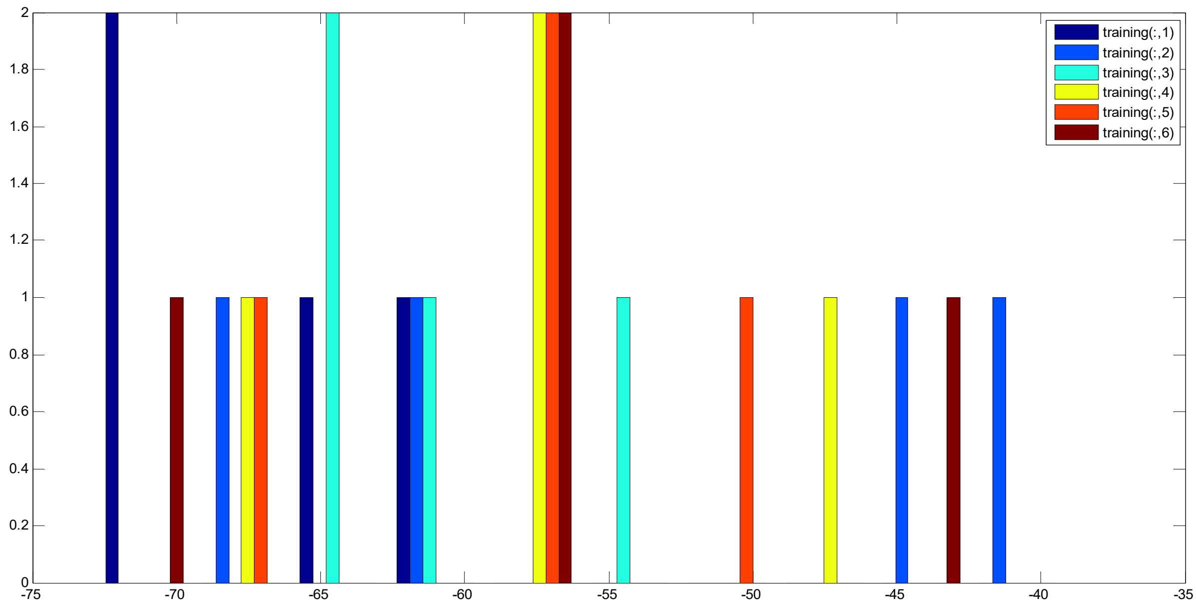

Fig. 9 Bar graph representation of the entire mean RSS stored for fingerprinting

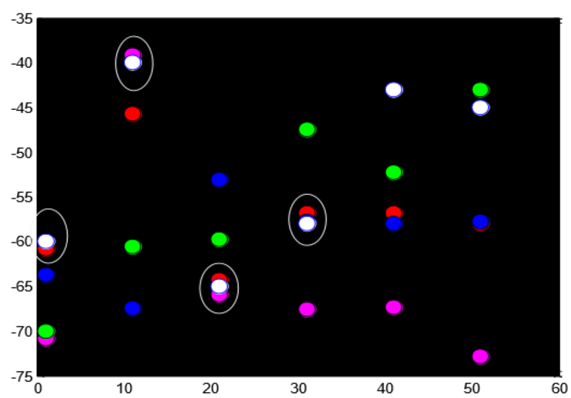

Fig. 10 Localization based on KNN

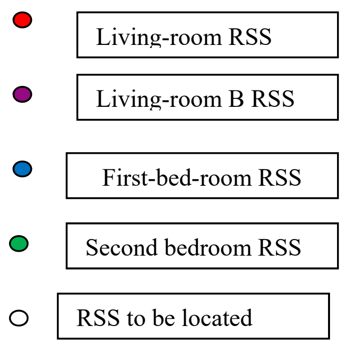

Fig. 11 Key showing RSS per room

One of the disadvantages of KNN algorithm in other areas of research is that it is a selfish algorithm: it focuses on the neighbors and does not extend the relationship to other extended neighbors. However, in the field of indoor localization the disadvantage becomes the greatest advantage and gives it the reason why it has often been used by many researchers in localization.

V. System Implementation

The overall system is composed of three parts, namely the Android side, server side and the website. Fig. 12 provides a graphical depiction of how the Android side and website interaction with the server. All the algorithms discussed above are coded based on Android/Java the tracking and location of the mobile device information are stored in SQLite database and cloud computing concurrently. The reason for using both databases is that Android provides a very Lite database that can be stored in SD card in the phone called SQLite; hence, when the main server(cloud) is down, we can use the SQLite database. The user side application is built based on Android/Java programming language, while for the server side application we used PHP, CSS and HTML.

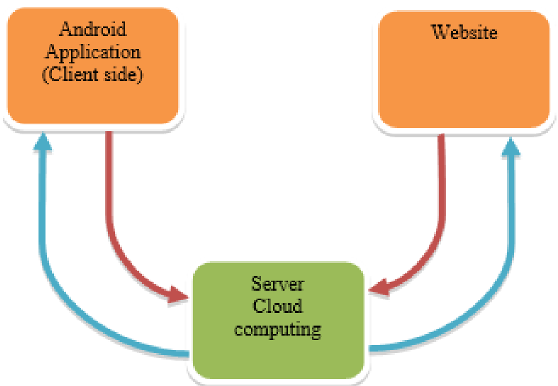

Fig. 12 Abstract System design

VI. Android Indoor Localization (Client Side/Android App) Implementation

On the client side is an Android application that runs on mobile phones. The application is dynamic in that it can be used in any building. The application allows you to specify the map and calculate the length and the width of the building with relation to the pixels. It also tracks the location of the mobile application based on sensor fusion algorithms and sends the information to the cloud. Figs. 13-15 show some of the graphical user interfaces for the client side.

Once you click quick scan on the home page application, it will direct you to the new fragment, which is the sensor calibration process. You need to tap the screen to record a step taken as you walk in order to for calibration to take place.

After calibration, we upload our map to the mobile active fragment. The map should mimic the building. Then we convert the length and width of our building in pixels. After setting the building map, the application is set to track the mobile device. The application will track the user and send the data about user location into the cloud server. The data being sent is in the form of images and location co-ordinates.

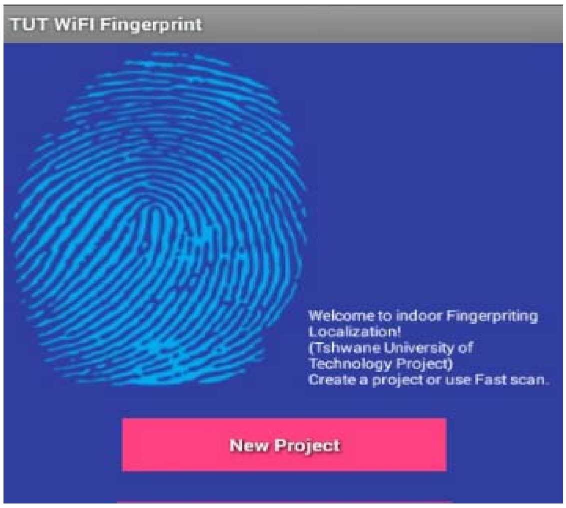

Fig. 13 Application Home page

Fig. 14 Automatic Sensor Calibration

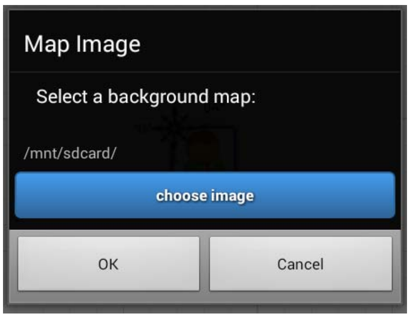

Fig. 15 Selecting Map

We used cloud-computing server to store our data. The main reason for using the cloud computing is that during disasters like fire, theft or terror, the authorities concerned are able to access the relevant information anywhere as long as there is an Internet connection. To access the cloud computing data, a secure website is developed. The website is built using PHP, JavaScript, HTML and CSS once logged in, to the website. The system refreshes after every 25seconds to allow data flow. Fig. 16 shows the login screen for the server side website.

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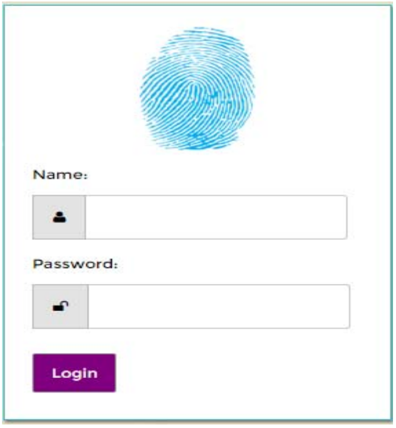


Fig. 16 Website Login Page

Fig. 17 Home Page

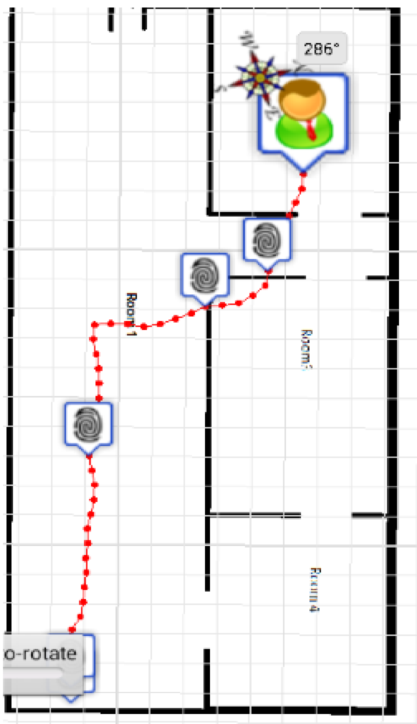
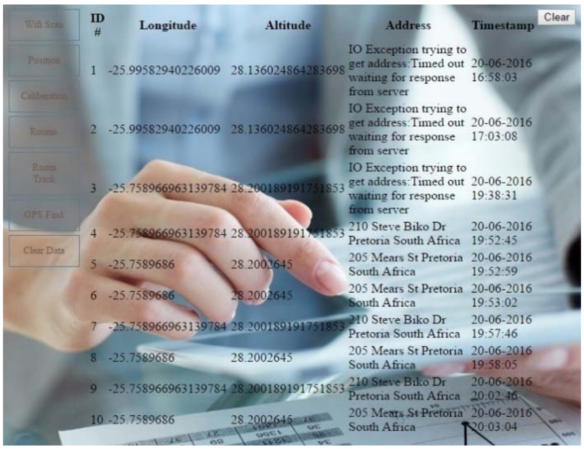


Fig. 18 Room Track clicked



ID #	Longitude	Altitude	Address	Timestamp
1	-25.99582940226009	28.136024864283698	IO Exception trying to get address:Timed out waiting for response from server	20-06-2016 16:58:03
2	-25.99582940226009	28.136024864283698	IO Exception trying to get address:Timed out waiting for response from server	20-06-2016 17:03:08
3	-25.758966963139784	28.200189191751853	IO Exception trying to get address:Timed out waiting for response from server	20-06-2016 19:38:31
4	-25.758966963139784	28.200189191751853	210 Steve Biko Dr Pretoria South Africa	20-06-2016 19:52:45
5	-25.7589686	28.2002645	205 Mears St Pretoria South Africa	20-06-2016 19:52:59
6	-25.7589686	28.2002645	205 Mears St Pretoria South Africa	20-06-2016 19:53:02
7	-25.758966963139784	28.200189191751853	210 Steve Biko Dr Pretoria South Africa	20-06-2016 19:57:46
8	-25.7589686	28.2002645	205 Mears St Pretoria South Africa	20-06-2016 19:58:05
9	-25.758966963139784	28.200189191751853	210 Steve Biko Dr Pretoria South Africa	20-06-2016 20:02:46
10	-25.7589686	28.2002645	205 Mears St Pretoria South Africa	20-06-2016 20:03:04

Fig. 19 Outdoor information

Fig. 17 shows the home page of the proposed system. It has seven buttons upon clicking does specific tasks, i.e. Wi-Fi scan button shows all the RSS based on AP within reach; position button will display the location of the mobile device; the calibration button will indicate all the data related to the sensor of the mobile device; the room button works as the position button though provides general location, such as the room where the mobile is; the room track button shows all the rooms the mobile device has been; while the GPS find button provides the street address, longitude, and latitude of the mobile devices, as shown in Fig. 19; and the clear button is used to delete the information from the database.

If the mobile device is no longer in the building under surveillance, the proposed system provides further information about the possible location where the mobile address might be such as a street address and building number, as shown in Fig. 18. This information is very relevant since we are dealing with mobile devices, since one is not static.

VII. Conclusion

The field of indoor localization and the field of digital forensics are far and apart. However, the proposed system tends to bring the relationship closer. This proposed system can be used during an investigation together information about a specific occurrence. It might be used during and after a disaster, e.g. terror attack, theft or fire evacuation. It provides basic information about the location of a specific Android mobile device that can be used as a stepping stone for further investigation, if one is not in the vicinity of the map. The application provides general information about the location of the mobile device, e.g. the street name and street address where the mobile device is. This information can then be used by investigating authorities to track and locate the mobile device both in the indoor and outdoor environment.

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