

Indoor Positioning System

Using Wi-Fi fingerprinting method

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Abstract : Indoor positioning system is a system which can determine the position or location of people in an indoor environment. In an indoor region, their location can be tracked by a third party. For indoor positioning, we have adopted a method known as fingerprinting. This method utilizes the existing Wi-Fi infrastructure, and works upon the signal strength from the Wi-Fi access points. The employment of access points for indoor location-based services in an exceeding indoor space, leverages their use. Fingerprinting involves generation of a database which contains signal strengths at every point in a decided area, which has been done using android application. Later, the position can be computed using this database and the incoming real-time signal strength values. Machine learning has been used to increase the accuracy of the system. The application is successfully generating the desired database and the system is able to track the signal strength received by the mobile devices acquired by the people, present in the local area.

IndexTerms - Indoor Positioning System, Fingerprinting, Wi-Fi, Access points, RSSI, Database, Machine learning.

I. INTRODUCTION

Nowadays, there are many organizations like corporate buildings, schools, colleges, shopping malls, showrooms, etc. where there is a requirement of indoor location based services for reasons like security and surveillance. So it becomes important to estimate the position of a user inside a building. The existence of mobile devices as a location pointing device using Global Positioning System (GPS) is a very common thing nowadays. The use of GPS as a tool to see the placement, in fact, incorporates a shortage once used inside. Indoor positioning techniques, using radio wave based approaches for localization will use completely different wireless technologies like Bluetooth, Wi-Fi, signals of cellular towers and ZigBee. Wi-Fi is the most popular. Wi-Fi networks are current in most public buildings and its use doesn't need an extra infrastructure.

There are various methods that have been proposed to implement indoor positioning. One of them is Wi-Fi trilateration approach. Trilateration is a concept that determines the absolute or relative locations by the measurement of distances, using pure mathematics. In this technique, three fastened points are required to see an inside position. The main plan is to calculate distances between access points (AP) and mobile device to produce a vicinity of localization. This distance is often provided by such signal measurement techniques sort of a received signal strength (RSS), time of arrival of radio signals from transmitters (ToA) or time difference of arrival of several radio signals (TDoA). But, a drawback of this approach is the system in trilateration method requires more maintenance and sometimes produces inaccurate results. We are designing an easy approach to maintain indoor positioning system and implement this system at very low cost. This is because we are designing this system on the existing infrastructure with no additional hardware requirement.

II. RELATED WORK

Our initial research to the problem statement is that there is inaccurate location provided by GPS. GPS location is influenced by various factors. Satellite positioning takes significant time to track moving objects. To locate us, we need a new form of wireless location determining technology. Some workable solutions mentioned in previous papers are:

I. Fingerprinting

This solution is based on Received Signal Strength Indication (RSSI) pattern. The RSSI pattern in a particular physical area will be recorded with available Access points (APs). Later, real-time RSSI values will be matched with existing pattern to predict the location this method is called as Fingerprinting.

II. Angle of Arrival (AoA)

This solution uses Angle of Arrival (AoA). AoA determines the direction by measuring the time difference of Arrival at individual elements of the array. By deriving the angle and determining radius by RSSI, the location can be tracked. [1]

III. Time of Arrival (ToA)

In this method, location can be directly calculated from the time of arrival as signals travel with known velocity derived from multiple APs, the position accuracy will increase. This solution uses Time of Arrival (ToA).

III. THE PROPOSED SYSTEM

In this paper, we have discussed the method of fingerprinting in detail and implementation methodology for achieving indoor positioning.

1. Wi-Fi fingerprinting

1.1 Calibration phase

For indoor positioning, we need to determine the position of people in an indoor environment. It can be a room, small or big, or a floor or entire building. Here, we need a system where the user is a third party, which is the respective authority. To design such a system, fingerprinting method is the best way. It utilizes the existing Wi-Fi infrastructure, and works upon the Received Signal Strength Indication (RSSI) from the Wi-Fi access points. The employment of access points for indoor location-based services in an exceeding indoor space, leverages their use. Fingerprinting involves generation of a database which contains RSSI values at every

point in our desired area. The points can be represented using the (x, y) coordinate system, in a convenient manner. This will form the first phase i.e. calibration phase, refer fig.1 Flow diagram of Fingerprinting technique. Later, while doing actual positioning of random people coming in and going out of the room, the RSSI values recorded by their mobile devices at that time, are sensed by the APs nearby. The APs then send these values in real-time to a server where our previously generated database exists. By utilizing all the information, position can be computed using an algorithm. The task of computation and prediction can be done on the same server by using Machine Learning algorithm. It will increase the accuracy of the system. This will form the positioning phase.

We are using known parameters of Wi-Fi networks like its signal strength, the network MAC-addresses and real coordinates of Wi-Fi access points in the location. The aggregator being used by us in the place of access points is used to collect the beacon frames of the user. Aggregator is an ESP8266 Wi-Fi integrated SoC which has custom firmware flashed in it to capture the beacon frame and extract probe request messages from the management beacon frame and will calculate the RSSI signal strength of the mobile and relay/forward it to the central server for processing. The fingerprinting database is generated using custom designed Android application, which will capture RSSI values at different position of the tracking area and generate a database in the form of a '.csv' file.

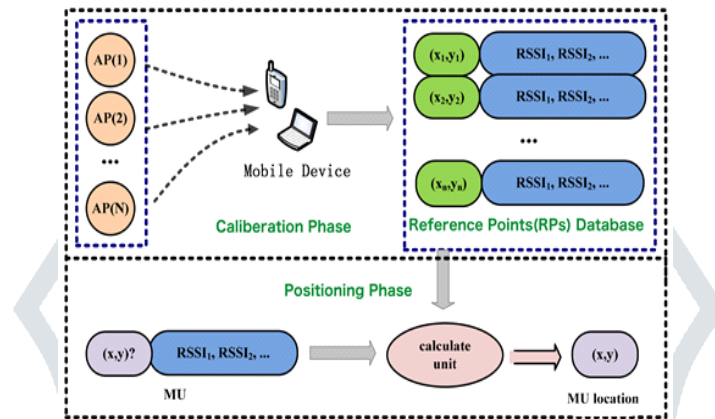


Figure1: Flow diagram of fingerprinting technique

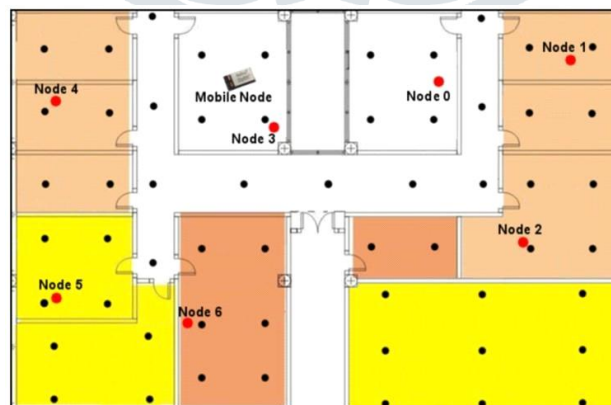
The app will generate the database for us by scanning all the available access points in the surrounding and will only record have assigned access points received signal strength of the targeted access points at different location at different instant. Multiple recording will make the training database file size more but the accuracy of the predicted result will be higher. The recorded access point's data at different location is mapped to the floor plan.

Figure 2. Fingerprint floor plan^[6]

Once the mapping is done then the dataset generated by the app is transferred to the ML algorithm to train the classifier on the generated dataset.

1.2. Positioning phase

While doing actual positioning of random people coming in and going out of the room or any indoor space, the RSSI values recorded by their mobile devices at that time, are sensed by the APs nearby. They sense this information using beacon frames that are continuously broadcasted by a wireless device for advertising to connect with surrounding APs. These beacon frames also



contain the RSSI recorded by the mobile device The APs then send these values in real-time to a server where our previously generated database exists. We are using ESP8266 that will act as our access point. We named it as 'aggregator' due to its function. It will collect the beacon frames of the user. Aggregator is an ESP8266 Wi-Fi integrated SoC which has custom firmware flashed in it to capture the beacon frame and extract probe request messages from the management beacon frame and will calculate the RSSI signal strength of the mobile and relay/forward it to the central server for processing.

By utilizing all the information, position can be computed using an algorithm known as KNN which is explained below. The task of computation and prediction can be done on the same server by using this Machine Learning algorithm. Also, it will increase the accuracy of the system. This will form the positioning phase.

2. K-Nearest Neighbor (KNN)

The principle of this algorithm is to assign membership as a function of the Euclidean distance vector from the basic K-NN algorithm and memberships in the probable label. The principle of this algorithm is to assign memberships as a function of the Euclidean distance vector from the basic K-NN algorithm and memberships in the probable label. The principle of this algorithm is to assign memberships as a function of the Euclidean distance vector from the basic K-NN algorithm and memberships in the probable label.

The principle of this algorithmic rule is to assign membership as to perform the Euclidian distance vector from the essential K-NN algorithmic rule and memberships within the probable label. The basic matching algorithmic rule wide accustomed to find the most effective classifier, really perform and non-parametric classification technique is that the K-NN algorithmic rule. In the process of online positioning step, the K-NN algorithm was used to search for K-neighbors closest between classes of training database and measure RSSI point based on Euclidean distance. Before we get into details of the K-NN we need to define the minimum distance using Euclidean distance based on Bayesian classifier^[2].

The KNN algorithm selects and combine the nearest K neighbors around a device to determine its position. Using a fastened variety (K) of fingerprints could decrease positioning accuracy: if K isn't modified throughout the positioning method, sometimes, access points far from the device might be included in the KNN algorithm. Therefore, eliminating some access points before applying the algorithm. Therefore, eliminating some access points before applying the positioning algorithmic rule seems necessary^[1].

KNN seems to be a good candidate for classification of this sort. It is due to the fact that KNN tries to make the classification by calculating the distance between features, while the intensity of various RSSI signals depends on the physical distance between Wi-Fi source and mobile phones. In this case, closeness in feature area could be a smart indication of closeness in physical area.

IV. RESULTS AND DISCUSSION

The fingerprinting database is generated using custom designed Android application, which will capture RSSI values at different positions of the tracking area and generate a database in the form of a '.csv' file.

We have to enter the location coordinates for each point inside the room and record RSSI value at each coordinate. The application saves the coordinates and their respective RSSI values recorded by our wireless mobile device from all nearby APs and shows them for respective APs on a single-click. Further by clicking on create database, it creates one and keep on adding more data to it. The app also has some more functions like auto increment, so that each time we do not enter the location coordinates manually. The application is shown is figure 3a & figure 3b.

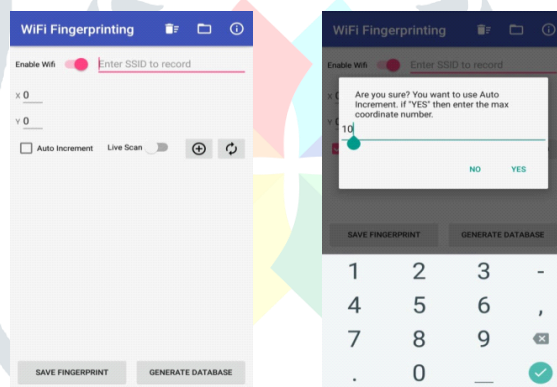


Figure 3a. Screenshots from Android Application

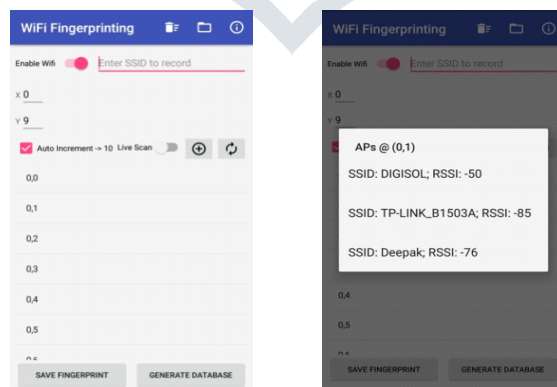


Figure3b: Application capturing RSSI values

1. Wi-Fi RSSI measurement collection

In presented paper signal strength levels was measured by distance of three access points allocated in the three rooms within the floor. This data is collected to points estimation for fingerprint method described above. These measurements are made in 15 points at the 1-meter interval for each access point using developed Android application. This application found three different access points by MAC addresses and measured the RSS levels 10 times for each of 15 distances for every access point. The RSS level changes at time therefore it is necessary to use its average value. The access point RSS levels are displayed in the Table I.

Distance, m	AP1 RSS, dBm	AP2 RSS, dBm	AP3 RSS, dBm
1	33.3	38.8	55.3
2	45.7	43.1	50.3
3	50.9	48.9	65.7
4	51.7	55.2	61.2
5	51.8	75.1	62,5
6	53.4	75.5	66.4
7	57.8	76.4	70.5
8	62.4	80.8	72.3
9	65.7	80.8	74.7
10	62.9	76.0	78.0
11	72.9	88.6	76.07
12	72.7	88.2	86.02
13	63.9	91.0	79.03
14	74.0	91.9	85.08
15	76.7	92.1	82.05

Table1: The RSSI results for three access points

The resulting application is able to perform all the functions required for the purpose of efficient calibration/tracking of an entire room showing good results. It is reading the RSSI values received by a mobile phone from the APs even when not connected to them.

2. Recorded data by Access point

```

COM4
20:05:37.766 -> json: {"probe":{}}
20:05:38.752 -> json: {"probe":{}}
20:05:39.783 -> json: {"probe":{}}
20:05:40.768 -> json: {"probe":{}}
20:05:41.753 -> json: {"probe":{}}
20:05:42.771 -> json: {"probe":{}}
20:05:43.756 -> json: {"probe":{}}
20:05:44.788 -> json: {"probe":{"address":"data:19:d6:64:4f","rssi":-81}, {"address":"data:19:d6:64:4f","rssi":-76}}
20:05:45.772 -> json: {"probe":{"address":"data:19:d6:64:4f","rssi":-71}}
20:05:46.790 -> json: {"probe":{}}
20:05:47.790 -> json: {"probe":{}}
20:05:48.775 -> json: {"probe":{}}
20:05:49.760 -> json: {"probe":{}}
20:05:50.793 -> json: {"probe":{}}
20:05:51.776 -> json: {"probe":{}}

```

Figure 4. Serial output from Aggregator

The output of our aggregator that is acting as an AP is recorded on a serial monitor as shown in the figure above. It is collecting the RSSI and MAC address of the device in the field.

3. Web interface for setup and monitoring

We have designed a specialized website known as WPS locate. It is the web interface to view the actual location of the desired mobile device on the screen. It will be used by the third party or the authority who have set up this indoor positioning system in their building. Its use will be restricted. Its access will be available only with the respective authorized people.

Following figures shows the web pages in different stages. Each of the web page contain description about the step being performed. There are guidelines given, to do the entire setup by performing all the steps one by one.

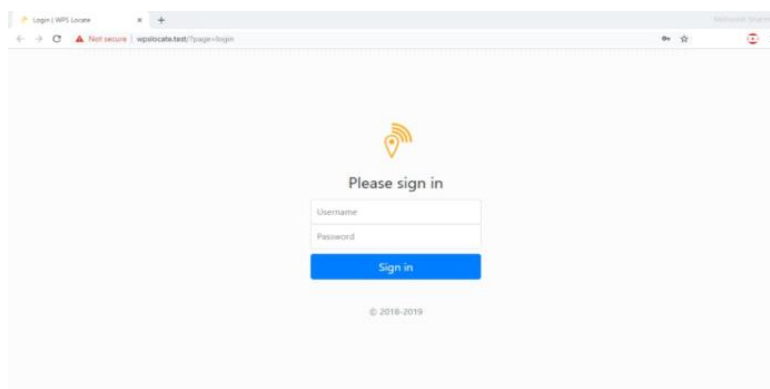


Figure 5. Sign in page

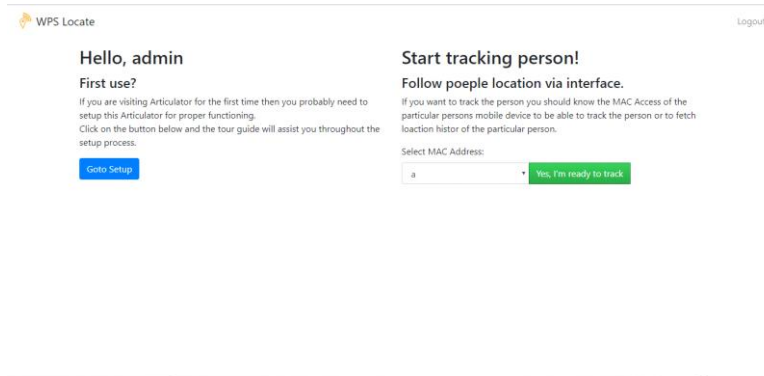


Figure 6. Admin main page

Admin page is shown in figure 6 is the main page home page where the user will land after sign in. there are two section in this page first is for setting up the system and second one is for tracking of specific user.

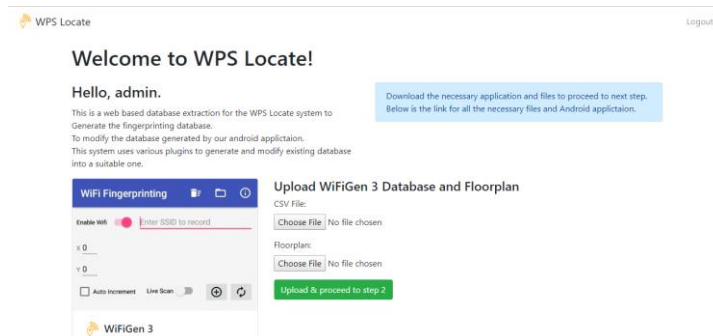


Figure 7. Uploading the database and floorplan (Step 1)

This page asks for the .csv file of the database generated by the application and the floor plan image of the area in which position has to be determined.



Figure 8. Mapping the location points onto floorplan (Step 2)

This step is for mapping location id tags to floor plan. This is GUI based location ID mapping system. This mapping will be further used for predicting location and for visual feedback to the user.

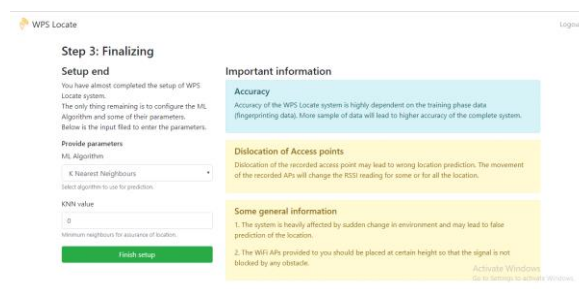


Figure 9. Selection of ML algorithm and parameter (Step 3)

Third step is finalizing after completing the setup of WPS Locate system. To configure the ML algorithm and enter the parameters. Click on finish setup.

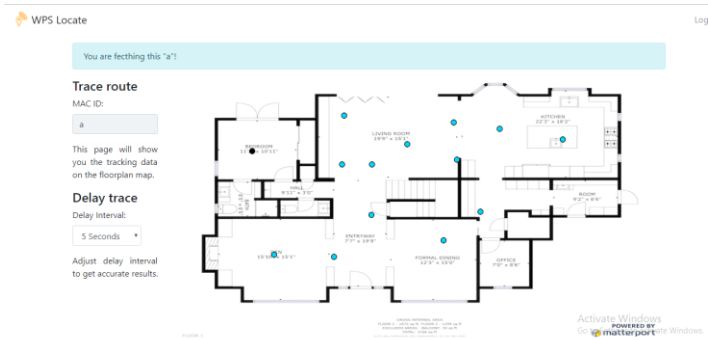


Figure 10. Prediction web interface

Select the MAC ID of the person to be traced and select the delay. The page will show you the tracking on the floorplan map. Adjust the delay settings for better and accurate results

V. CONCLUSION

The fingerprinting method works effectively and gives desirable result. There are some factors which may cause a decrease in accuracy of the results. We need to consider all such factors, we need to improve the system more in order to increase the accuracy of tracking in order to achieve desired result.

The instability of RSS in indoor environments is the major challenge for RSS-based WLAN positioning systems.^[3] The first reason is the structure of the indoor environment and the presence of different obstacles, such as walls, doors and metal furniture etc. Also the RSS value varies over time, even taken at the same location.

Many devices such as microwave ovens, smart-phones, laptops another wireless signal transmitters. In the calibration phase, which is used for Collecting the RSS data and storing the corresponding location information in a database, these devices will likely lead to radio interference and make the wireless signal strength fluctuate.^[5]

Furthermore, normal human body can also affect the WLAN signal strength. The RSS values on the straight line between the smart-phone and an access point (AP) will be influenced by the body of the person. We have overcome this by taking multiple RSSI reading to decrease the error.

VI. ACKNOWLEDGMENT

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