Indoor Location System with Wi-Fi and Alternative Cellular Network Signal

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Abstract

Wi-Fi positioning system is widely being studied in many fields of smartphones. In an open air environment a GPS receiver is able to determine its position with a high level accuracy. But in inside a building, where the GPS signal is bad or unavailable or unappreciated. The position estimation from the GPS receiver is very erroneous and has no practical use. Wi-Fi triangulation system is applied in indoor location but faced signal coverage error. Therefore, we propose a method of indoor positioning that determines the user's current position with the nearby Wi-Fi routers and cellular network signal strength RSSI values. This Signal strength RSSI estimates the location fingerprints based on at least two wireless Access Points and an alternative Cellular network or three access points. The cellular network is an alternative backup of unreached Wi-Fi Access point where this Access point's coverage is unknown or sparse. Predefined points are used to measure distance from a user could also generate advance level accuracy. Referring to the floor map, our method adjusts the real-time user's current location. Gravity sensor works on the back end to control Wi-Fi scanning enable or disable considering user movement for energy efficiency. We have implemented the proposed method on Android smart phones and our test results are discussed in this paper.

Keywords: Wi-Fi RSSI values, Wi-Fi triangulation, Cellular network, Gravity sensor

1. Introduction

In an unknown environment the information from the GPS can help a user to achieve, a destination with minimal support from the environs within a relatively small period of time. But this GPS (Global Positioning System) is not accurate in all unknown environments. It operates poorly in indoor environments rather than outside [1]. The WLAN and sensor based indoor positioning is widely used because WLAN is available virtually everywhere and sensor are with smartphone [2].

There is a problem that exists in indoor environment which happens when transmitted signal from Wi-Fi access point is reflected due to barriers such as building walls or other abstracts [3].

Figure 1 reflected the Wi-Fi triangulation of a device covering three Access points. All three are covered the device with the full ranged estimate power signal strength.





Wi-Fi Positioning concepts will affect due to no signal of any access point and also involves the accuracy of the location. The cellular network provider could be a backup of this unreached access point which working on the base of RSSI signal strength showing in Figure 2. Moreover, an outdoor location also could work for finding longitude and latitude.



Figure 2. Two Wi-Fi Access Points and Network Provider Coverage

The chief contribution of our mobile application could appraise to examine the degree of accuracy that could be accomplished with the estimated signal strength of Wi-Fi and network provider strength. It also adjusts the estimated current location with information represented on the 2D floor map. Our test results showed that our indoor positioning app is very accurate without access to the internet.

In this paper, we propose a personal indoor WPS and alternative cellular network system on the smartphone using RSSI signal strength. Signals from cellular network are the alternative of any enriched Wi-Fi access points and also predefined points [4] used for comparing to the know distance to make suitable adjustment. Gravity sensor, extra feature for controlling Wi-Fi scanning enable or disable in Wi-Fi powered mode for battery efficiency [5]. Section 2 representing related works which is working behind this indoor navigation. In Section 3, a description of our proposed algorithm for tracking the position is presented. In Section 4 and Section 5, we discussed the tested and accuracy measurement and database construction. Implementation of the algorithm and the results of experiments are described in Section 6. In Section 7, we conclude the paper.

2. Related Works

Indoor positioning is an actively experimentation field. There are many recommendations that are closely related to our effort. Sound-based positioning mentioning sound fingerprinting uses ambient sound system to generate user position, whereas active fingerprints are recorded in a specific sound pattern for the positioning. This method proposed an approach to estimate the relative distance between two devices and classified in three distance regions (0m, 0m - 12m, 12m - 48m) [6]. Comparing ambient sound provided the fingerprints which recorded from the devices' positions with an accuracy of 81%. No absolute position report was obtained by this method.

A new smartphone-based indoor positioning system proposed to determine user's moving direction with both magnetometer and gyroscope measurements [7]. The system measure the number of steps taken by the user with accelerometer values. The number of steps created the distance that the user moved. With the direction and the distance, the system provides the user's current location. Sensors not supported to all smartphones are the limitation.

Wi-Fi signal system for the indoor localization task already exists. Here, the signal strength of Wi-Fi station is used to determine the position of a mobile device. Mainly, wireless infrastructure, localization accuracy depends on the signal strength of Wi-Fi access points in the environment. *E.g.*, Haeberlen *et. al.*, presents an accuracy of 92% [8]. Three or more than Wi-Fi stations are required for all appraisals. This method faced an ineffective positioning approach that at least three Wi-Fi stations are needed for coverage.

In our activities, we propose to use an alternative Wireless approaches such as cellular network signals and Wi-Fi signals. Every fingerprinting based on, at least two ranged Wi-Fi APs and an alternative cellular network for any no ranged Wi-Fi AP.



3. Indoor Positioning Algorithm

Figure 3. Flowchart of Indoor Positioning Algorithm

Indoor position detection using Wi-Fi signal strength based on the concept of GPS system [9]. Minimum of three access points (AP) are needed to determine the position of a user in an indoor location. Figure 3 shows a flowchart that a device scans for three RSSIs from each AP in every .6 seconds of time interval. Wi-Fi scanning is controlled by gravity sensor in Wi-Fi enables mode to verify user movement. If the device got three Wi-Fi APs than the mean value of three RSSI is calculated. An alternative cellular network RSSI value would be included if any access point is obscure or sparse. If Any Access point is not

in range than cellular network RSSI value will add and make three RSSI values like triangulation. The user location point is determinate by calculating the difference between the mean of the three RSSI values with each value stored in the database and also compared to predefined position points. Thus the accuracy ready of the device can be compared to the know the distance and this data can be used in navigation system to make proper location on the map.

4. Tested and Accuracy Measurement

Figure 4 represents the part of the 2nd floor plan of the CSE building of the Chittagong Engineering University used during the testing. The floor contains mainly of classroom, conference rooms, electronic labs and computer labs. Yellow marks represent the location where the Access Points are positioned. Three Wi-Fi Aps were installed for the experiment and a cellular network is working inside of a university.



Figure 4. Building with Three APs Position

Figure 5 represents the measured Wi-Fi signal strength for all APs. The measuring is done using user holding the phone in the hand, and pointing all places in the map. These values represent the measuring 3 signal RSSI at each test point. At point (AP1, AP2, and AP3) is sporting to three Wi-Fi signals in each direction respectively. On the other hand (AP1, AP2, CN) is representing two any Wi-Fi signal's RSSI and another is Cellular network signal's RSSI value. This will be running on the basis of absence of any one Wi-Fi signal. Here, AP3 is unreachable and the Figure 5 showing this.



Figure 5. Three Wi-Fi and Cellular Network Combination Fingerprint



Figure 6. Low AP Signal of Wi-Fi Triangulation

Figure 6 shows signal intensity level of single point of AP1, AP2, CN (in Figure 5). This point observed a low strength of AP3. This lower strength caused a huge difference to calculate mean value. Figure 7 mentioning the removal this situation using alternative cellular network (CN) signal.



Figure 7. Alternative CN with another 2 Aps

A real-time signal strength variation recorded over a period of approximately .1 second. The signal measurement is shown in Figure 6. Here three APs signal strength RSSI fingerprints are mentioning.



Figure 8. Three Signal RSSIs

The user creates the RSSI fingerprints and records as temporary stores which are utilized for the Wi-Fi position estimation range. At the current point the average RSSI value of three measurements is saved for every visible AP and also included cellular network in the absence of any AP. Figure 7 mentioning the average signal and a range of signal maximum value and the minimum value. The records compare with their coordinates which are stored in the database.



Figure 9. Every Signal Means with Some Values

The signal strength is not constant at a fixed level and it varies over a period of time [10]. Here the measuring fingerprint values remain in a range. So, that the maximum potential error is in equation 1.

 $\mathbf{Error} = |signal_{max} - signal_{min}| \qquad (1)$

Based on fuzzy logic [11] using the mean of every AP signal strength value at each point the possible fault is cut according to equation 2 and 3.

$$\begin{array}{l} \mathbf{Error_1} = |signal_{max} - signal_{mean}| \quad (2) \\ Or: \\ \mathbf{Error_2} = |signal_{mean} - signal_{min}| \quad (3) \end{array}$$

Working out all errors with the respect on three access points it can set in Figure 10. In the full ranged signal area, it could show 90% old and new accuracy. In the point of low signal of any access point it shows the 50% accuracy in old and new. It's based on any undefended signal and created large comparable value with database comparison. APs with alternative CN signal proved the effectiveness and up this accuracy into 90%.



Figure 10. Accuracy with All APs and CN

For better Accuracy our model continuously compares the signal from the predefined position. Predefined points indicate the known signal strength of all three APs or alternative CN represented by coordinates (xi, yi, zi) where $i = \{1 \text{ to } n\}$ in figure 11.Each Ri value represent the distance from the reference point to user position P(x, y, z).Thus the accuracy ready by the device and this data can be used in navigation system to make suitable adjustment in 10% advanced.



Figure 11. Smart Device Position P(x, y, z) Signal Compare with Predefined Points

Comparison of existing model with our suggested model is depicted in Figure 12. Accuracy and effectiveness are defined in three portions. Our proposed model used database tacking values similar to the living model for navigation, but advanced accuracy, it proposed predefined points to get 10% from earlier. Alternative CN signal achieves 98% efficiency. Sensor based Wi-Fi scanning controlling dependent on user movement save 10% battery life.



Figure 12. Advanced Accuracy and Effectiveness of our Proposed Model Comparison with Existing Model

5. Database Construction

The signal intensity is either reflected or blocked, due to reflections from the walls, floor and clutch, or other structures in the building [12]. Resulting in different signal strength measured at the same level. Our signal strength variations recorded over a period of approximately 0.1 second and continue until six times. Every time its take 0.6 seconds to calculated mean of all data, showing in Table 1.

Access points	RSSI 1	RSSI 2	RSSI 3	RSSI 4	RSSI 5	RSSI 6	Mean
AP1	-44	-46	-44	-50	-47	-45	-46
AP2	-77	-78	-73	-76	-73	-78	-76
AP3	-83	-86	-84	-83	-87	-87	-85

Table 1. Three APs 6 Time RSSI Signals

Table 1 representing the three access point six times RSSI fingerprints which interval over a 0.6 second and including cellular network RSSI showing in Table 2.

Access points	RSSI 1	RSSI 2	RSSI 3	RSSI 4	RSSI 5	RSSI 6	Mean
AP1	-55	-56	-54	-53	-57	-55	-55
AP2	-92	-98	-93	-98	-94	-95	-95
CN	-83	-86	-84	-83	-87	-87	-85

Table 2. Two APs and one CN 6 Time RSSI Signals

Table 3 represents the Maximum and Minimum RSSI values with the corresponding point X, Y mobile screen direction. As the Application runs the Wi-Fi is scanned with an average .6 second intervals, the measured values compared with the corresponding point storage data. Then it selected to estimate the current coordinates of the phone's position.

RSSI no	Database Max RSSI	Database Min RSSI	Acquired Mean RSSI	screen (X,Y) position
RSSI 1	-42	-48	-46	
RSSI 2	-72	-79	-76	(100,30)
RSSI 3	-81	-87	-85	

Table 3. Three APs 3 Time RSSI Signals and Mean Value

6. Implementation

We develop an Android-based smartphone Application. The user interface is shown as a home page with scan Wi-Fi APs or Cellular network signal RSSIs showing in Figure 13. There are three buttons. Frist one is a start button that calculates the smartphone to current location with signal RSSI in 0.1 interval timing. The Second button is working to upload floor maps depending on building flooring.



Figure 13. Home Screen of the Application

The map is an icon, a conversion from cm to pixels. These pixels per meter are measured. Last one uploads a file with positioning data with X, Y screen coordinates. The coordinates are multiplied by this factor and the map the coordinates on the screen where the map image starts are added. Figure 14 displays a map and user location point with an indicator on the screen. Expression of (X, Y), representing the position of indicator on screen. Figure 15 represents the phone's position with a floor map. Here X, Y values are stored in testing time with corresponding of max and min values.



Figure 14. (X, Y) Positioning in Building Map in Mobile



Figure 15. User Positioning in Building Map in Mobile

The position would be updated based on Wi-Fi and Cellular network only and some predefined points. The position is updated based on the mean of the last 6 readings of the Wi-Fi or network provider signal. Figure 16 shows the results. When user motion is detected again the position of the indicator, estimated comparing the data which was given by. It could calculate every new location within 0.6 second and so that it achieves the sufficient 91% accuracy in the indoor navigation system. Regarding battery life, gravity sensor barely performed in a back end to indicate user movement to disable scanning in WI-Fi enable mode.



Figure 16. User Position Updating in Building Map in Mobile

7. Conclusion

This paper presents an indoor localization system has an ability to execute using only Wi-Fi signals or Wi-Fi and cellular network both combines signal. This Application is easy to implement and requires lower cost with at least two access points. Specifically, we proposed a new algorithm to filter error signals using alternative cellular network signal. These algorithms offer a trade-off between detection accuracy and energy efficiency. It works out a proper scan time as a 0.1 second interval and reduces error rates. With some experiment on this application in our building of CSE department and consulting in different buildings we could state that it is close to 90% efficient in positioning and 6-10% increase in energy saving.

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