Design of IoT Based Object Tracking System for Identifying the RSS Value Access Point to Trilaterate the Location

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Abstract. In an expansive environment, due to continuous change of location of objects, tracking a moving object is a challenging task, in intelligent IoT service provisioned. Tracking of objects indoors using conventional methods like GPS can give out signals not as accurately as we get outside due to the signal attenuation, thus GPS gets poor results, moreover, the inclusion of other effective positioning modules increases the overall cost of production of the device. Nowadays, Wi-Fi networks are prevalent in most public buildings and do not require any additional infrastructure, so we have come with an idea of this is that we could propose an efficient and reliable Wi-Fi real time tracking system with help access points and signals strength. We are using a combination of two approaches where the first one uses pre-recorded received signal strengths. From the access points, and data is transmitted from the user on the move. It is known as the fingerprinting method. The second approach is trilateration from the known access points coordinates from the user’s device to find the position. The combination of these steps improves the accuracy of the user position in an indoor environment. The experiments presented in this research helps us understand and provide the source of a foundation for the indoor/outdoor positioning.

Keywords: IoT; Tracking; Indoor/Outdoor Applications; Access Point; Received Signal Strength

1. Introduction
In recent years we have seen the widespread use of outdoor positioning systems like GPS, being included in regular gadgets used in our day to day lives like smartphones and tablets. At the same time, outdoor positioning has been nicely adapted by the general public, its indoor counterpart has been usually restrained to personal use because of its higher expenses and complex setup requirements. The objective of this study is to offer a cheap means for indoor localization using WLAN. We blended two different wireless methodologies to locate a person. The primary technique entails the usage of matching the pre-recorded received signal strength (RSS) from close by Access Points (AP), to the information received
from the person on the move. This is generally called “fingerprint matching”. The second approach is a distance-based trilateration approach that uses the known AP coordinates detected at the person’s device to derive the location. The combination of these two processes enhances the accuracy of the user position in indoor surroundings permitting Location Based Services (LBS) like that of Mobile Augmented Reality (MAR) to be deployed greater accuracy inside the indoor environment. The mapping of the RSS map also can be useful to IT employees for covering places without wireless coverage (i.e. dead spots). The experiments were done in this study to help offer a foundation for the combination of indoor with outdoor positioning to create an overall smooth experience for the user as well as improved indoor usage of LBS technology.

The main goal of the literature review was to learn about pre-existing methods of indoor tracking and to gain an insight into the techniques used in them. Furthermore, the gaps in these studies were analyzed to help with the making of our system. Many studies were carried out in the area of improving indoor position accuracy and tracking. To name a few Anugrah et al., [1] conducted an online visualization work using RSSI- Kalman, and trilateration philters. Traditionally, the method of localization is based on GPS. However, in the non-line of sight (NLOS), GPS technology does not work as well as an indoor or mountain spot. The other approach is by LoRa technologies to introduce the localization method. The radiofrequency used in this application was to communicate with each other. Sadowski et al., [2] used unforgettable and portable methods to find items indoors via the telephone. The author analyses strategies in three common IoT wireless systems: Bluetooth Low Energy, Zigbee, and WiFi, along with three experimental scenarios in different settings to check performance. KNN is the most reliable and detailed localization technology, according to experimental findings.

Kalaichelvi et al., [3] performed a project to map and space victim position using iBeacon using an IoT-based framework. This thesis suggests a BLE and human protection symbol architecture for real-time monitoring. It deploys the machine fitted with BLE and receives the signal from the ibeacon computer. This makes it possible to map the precise position of the user by understanding the system user's RSSI value. Gala et al., [4] carried out a study for monitoring supported healthcare facilities indoor in real-time. The authors propose a method to locate and track an elderly person in an indoor environment in real-time using only existing Wi-Fi facilities. This paper explores designing an open-source software system that can identify a person with 802.11 Wi-Fi within 3 m precision in strong coverage areas.

Shi et al., [5] performed work to improve the placement of RSSI classifications and monitoring algorithms. This paper suggested a tripartite description of RSSI with its RSSI philter tracing algorithm. The proposed philter presents a function usable when small test RSSI samples are given a lower deviation from a large RSSI sample, obtained approximately 10 minutes, of less than 1dBm and when a sample count is greater than 20, the RSSIs are subclassified to the usual distribution. In a multi-story house, Logan et al., [6] performed work to establish the indoor location of a phone caller. The stated approach can be extended to non-BlueTooth RF issuers, including wireless link points. The findings of tests done in a live classroom building where iBeacons are used show 100% specific floor detection and average distance precision within five meters.

As we rapidly develop our mobile communication and computer technology [7], the requirements of location tracking are coming into play, as we can see there are dramatic change and improvements in mobile technology [8] to become fast adopted at all times, we as saw a lot of downsizing of computer hardware like wireless networking, batteries, and CPUs, this has helped the manufacturers to build mobile devices which can be carried around. That has brought us to the position of using location-based services it offers the location-dependent information to the user according to the needs [9]. So nowadays the Global positioning systems (GPS) can give us reliable position information for the location services [10], but the thing with where GPS cannot excel is that it cannot show us accurate information in closed
environments such as buildings and urban areas since there is signal degradation happening. So the objective is all about making an accurate and reliable system [11] which provides us location services. GPS systems and other sensors are not accurate in given conditions, which brings us to the idea of using Wi-Fi signals to determine the location [12]. The technique is that using it uses Wi-Fi routers which act as Access points and depending on that the smart devices measure the distance relative to the access points of Wi-Fi routers and determine the location of the devices.

The secondary objective is Indoor localization with help of Wi-Fi systems, the use of Wi-Fi to determine location is a great approach since Wi-Fi access points are abundantly available in today's scenario and it is possible to use the smart devices access them [13]. By using different techniques, we can analyze the location of the user. From the above table, we can see the characteristics and main advantages and disadvantages of the location tracking methods used in smart devices. GPS has high accuracy which leads to location tracking, along with the A-GPS (assisted-GPS) is a system where is it’s been used when the receiver is in remote areas and where the signals of the satellite can’t penetrate. Both GPS and A-GPS need satellite as its medium to work, it needs a high line of sight (LOS), to support accurate positioning [14]. Whereas the Wi-Fi positioning and INS can provide medium accuracy without any line of sight, they are more suitable for indoor environments, but the inertial navigation system (INS) has issued since it is prone to rapid accumulative errors.

2. Methodology

From the literature review and research, we came with few methods for estimating the location for indoor smart devices with help of Wi-Fi networks. They are the trilateration method and fingerprinting method. The trilateration method is globally used for surveying and Global positioning system; it uses the distances of a device from three or more access points or fixed points of the Wi-Fi signal. As shown in Figure 1, there is a smart device and access points (d1, d2, d3). Now the received signals are converted into distances which are the radii of the circle from the access points [15].

Since there are lots of complexity in indoor spaces, that impact the strength of the signal when those are converted into spatial distances, to reduce that there is this advance method called assist trilateration, these are subjects we are still researching. The main advantage of the fingerprinting method is that it uses existing WLAN infrastructure to determine the location of the device (Figure 2). Compared to trilateration, this method is more accurate and is relatively easier to deploy [16]. This method is based
on the relationship between the location and its corresponding radio signature. When the reference points (RP) are calibrated, they have a unique RSS reading (Reference Signal Strength) from the APs (Access point) and this is referred to as the fingerprint of that point. The RSS for many RPs in the AOI (Area of Interest) is collected during the calibration face and stored in a database. Then during the positioning phase, the Real-time RSS is compared with the database using different fingerprinting algorithms like deterministic or probabilistic algorithms. Some deterministic algorithms are the Nearest Neighbors (NN) algorithm, K-Nearest Neighbors (KNN) algorithm, Weighted K-Nearest Neighbors algorithm. After the first review, we decided to combine the above two methods to achieve improved accuracy.

Combination of Fingerprinting and Trilateration- Our approach involves the combination of the above two methods. First, the fingerprinting method is used to set up the APs and the database with all the available APs is created for all the reference points. At the time of operation, the fingerprint of the device location is used to determine its approximate location from the nearest APs. Then using the nearest APs signal strength, trilateration is done to determine the device location [17]. First, the RSS values of the locations are acquired using open-source software called Vistumbler. Then the database is created for each location by storing the location’s respective RSS values. Then using the real-time RSS values, the nearest APs are determined. Using the Path loss function, the distance between the APs and the device can be determined. Figure 3 shows the methodology flowchart.

3. Distance Computation Using Path Loss

\[ PL = PL_{IM} + 10 \log(d^p) + s \]  

Where,
PL = Path loss between sender and receiver
PL_{1M} = path loss at distance 1 meter away
d = distance between sender and receiver
n = path loss exponent in environment
s = standard deviation of signal strength variability

Using these distances and the equation of circles, we can find the point of intersection of the three circles drawn using the distance as radius from the respective Aps.

\[(x-x_1)^2 + (y-y_1)^2 = r_1^2\]  \hspace{1cm} (2)
\[(x-x_2)^2 + (y-y_2)^2 = r_2^2\]  \hspace{1cm} (3)
\[(x-x_3)^2 + (y-y_3)^2 = r_3^2\]  \hspace{1cm} (4)

We can expand out the squares in each one:

\[x^2 - 2x_1x + x_1^2 + y^2 - 2y_1y + y_1^2 = r_1^2\]  \hspace{1cm} (5)
\[x^2 - 2x_2x + x_2^2 + y^2 - 2y_2y + y_2^2 = r_2^2\]  \hspace{1cm} (6)
\[x^2 - 2x_3x + x_3^2 + y^2 - 2y_3y + y_3^2 = r_3^2\]  \hspace{1cm} (7)

If we subtract the second equation from the first, we get
\[(-2x_1 + 2x_2)x + (-2y_1 + 2y_2)y = r_1^2 - r_2^2 - x_1^2 + x_2^2 - y_1^2 + y_2^2\]  \hspace{1cm} (8)

Likewise, subtracting the third equation from the second,
\[(-2x_2 + 2x_3)x + (-2y_2 + 2y_3)y = r_2^2 - r_3^2 - x_2^2 + x_3^2 - y_2^2 + y_3^2\]  \hspace{1cm} (9)

This is a system of two equations in two unknowns:

\[Ax + By = C\]  \hspace{1cm} (10)
\[Dx + Ey = F\]  \hspace{1cm} (11)

which has the solution:
\[x = (CE - FB)/(EA - BD)\]  \hspace{1cm} (12)
\[y = (CD - AF)/(BD - AE)\]  \hspace{1cm} (13)

The point (X,Y) gives us the device position relative to the reference AP.

4. Experimental Study
The experimental setup was made using three APs located at different points of the house shown in fig. The distance between the three APs was noted and the floor map of the entire house was created for this experiment (Figure 4). The RSS values were taken from different points in the house (P1, P2, P3, P4, and P5) and were tabulated in the table. For the experiment, AP1 is taken as the origin and the other APs positions are taken respective to AP1 (Table 1). The scale used is 1 meter = 1 unit. By inputting the RSS values and the AP location values in the program the path loss can be determined. From this, we can find the distance of the device from the respective AP. By plotting circles using the device distance from the APs with the AP locations as the center points, we can determine the area within which the device is located.

| Reference Points | RSS values from the AP’s at the reference point from the experiment taken (dBm) |
|------------------|--------------------------------------------------------------------------------------------------|
|                  | AP1     | AP2     | AP3     |
| P1               | -52     | -46     | -40     |
| P2               | -48     | -44     | -67     |
| P3               | -66     | -44     | -46     |
| P4               | -59     | -60     | -45     |
| P5               | -75     | -63     | -43     |
5. Results and Discussion
The result of our experimentation with the above-given datasets which were acquired experimentally gives us an accuracy of < 1.3 meters. The common area between the three circles in Figures 5 to 9 below defines the area within which the device is located.

Figure 5. Graphical result for Access Point 1

Figure 6. Graphical result for Access Point 2

Figure 7. Graphical result for Access Point 3

Figure 8. Graphical result for Access Point 4

The graph (Figure 5) is obtained for the first reference point P1 from Table 1 when the RSS values for that point are used to trilateration the location of the device. The graph (Figure 6) is obtained for the first reference point P2 from Table 1 when the RSS values for that point are used to trilateration the location of the device. The graph (Figure 7) is obtained for the first reference point P3 from Table 1 when the RSS values for that point are used to trilateration the location of the device. The graph (Figure 8) is obtained for the first reference point P4 from Table 1 when the RSS values for that point are used to trilateration the location of the device. The graph (Figure 9) is obtained for the first reference point P5 from Table 1 when the RSS values for that point are used to trilateration the location of the device [18-20]. The findings suggest that when positioning is achieved with the high and medium loss of body humans, the positioning errors are high. One or more of the following factors may cause such a mistake. First, the human body induces absorption of the signals and shadows, which affects the signal frequency inevitably. In essence, the RSS shift induces errors of placement. Secondly, the suggested solution is based on the intersection and overlapping definition for the AP which is expected to contribute to a
narrower intersection area because of the greater number of available APs at a given point. However, the intersection might not be inherently small if the APs are relatively near situated. Since their coverage range might be somewhat similar if the APs are geographically nearby. This can lead to a major mistake in the expected position. Similarly, if the APs are remotely diffused, intersections cannot suffice to minimize the approximate room, contributing to a higher location error. The findings show fast and precise and consistent indoor real-time positioning with a range of about less than 1.3 m for indoor house environments.

![Graphical result for Access Point 5](image)

Figure 9. Graphical result for Access Point 5

6. Conclusion
In this study, real-time RSS is compared with the database using different fingerprinting algorithms like deterministic or probabilistic algorithms. The algorithms like Nearest Neighbors (NN) algorithm, K-Nearest Neighbors (KNN) algorithm, Weighted K-Nearest Neighbors algorithm were computed together and it’s combined to achieve a consistent indoor real-time positioning with a range of about less than 1.3 m for indoor house environments. In addition to existing external positioning equipment, indoor localization techniques allow for a complete indoor/outdoor spatial coverage that can greatly enhance the consumer experience. In comparison, location-based technologies, such as indoor navigation or enhanced fact, may provide more detailed indoor localization.

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