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IBPS: iBeacons Based Improved Indoor Positioning System

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***Abstract:** Smartphone plays a key role in integrating the entire world into a small hand. This feature made these smartphones as another human organ of many people. One of the main feature in every smart phone is GPS which used to travel new places, to locate and find optimized way to reach their destination. As we aware GPS is an outdoor application, GPS location is not accurate in indoor and small scale areas. This leads to an advanced research to improve the accuracy in GPS positing for the benefit of indoor applications. This research proposes a new iBeacons based Improved Indoor Positioning System for indoor positing application using Bluetooth low energy (BLE) beacons. This model helps the mobile application to find the exact location at micro-level scale. The objective of this research work is to design a potable indoor positing system (IPS) for indoor applications with at least 100m accuracy with in the inbuilt energy resource limitations. The proposed model has been built and verified in all the aspects. The location accuracy and energy efficiency of the proposed model is compared and found better than the existing models.*

***Keywords:** Indoor Position System; Low Energy Beacons Routing; GPS; Localization; RSSI; Bluetooth.*

I. INTRODUCTION

Real-time object tracing or a person tracking is not possible without help of GPS in current scenario. However, GPS signals are unable to penetrate the physical barriers in indoor environments. Hence the indoor positing system (IPS) takes place in the indoor application to track the object or position.

Indoor Positioning is an increasingly interesting topic nowadays. As satellite-based navigation technology has improved, outdoor positioning has become a de-facto feature in many products. Companies now deploy maps extensively for tracking and navigation, and there is a growing focus on how the same can be done indoors. There is a lot of active research in this area, and a lot of approaches have been proposed, such as using the Bluetooth Low Energy beacons, using Wi-Fi Access Points, and with magnetic fingerprinting.

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Other examples include infra-red sensing and sensor fusion technologies.

The overview of the proposed model consists of iBeacon transducers, an android mobile phone and a beacon. In addition to this, the proposed model uses the least square mechanism and triangulation. The proposed model employees on the captured signals as the sensory information to recognize and triangulate the position of an object. In this research, we evaluate Bluetooth Low Energy (BLE) Beacons acting as the primary technology for indoor positioning, and discuss its advantages and disadvantages. At the end, we present the results of our evaluation.

II. BLUETOOTH LOW ENERGY AND RSSI

A. Low energy Bluetooth

BLE shows a lot of promise in the form of a low powered wireless network. The hardware is portable, easy to deploy, and readily available. Nearly all smartphones today support BLE and there is a large developer community. A beacon is a BLE hardware capable of advertising data at regular intervals. A smartphone can listen to a beacon and get data from the beacon without a physical connection. This means that a smartphone can listen to a lot of beacons at the same time, getting all the nearby data quickly and easily. This connection-less data transfer is the biggest strength of the beacons.

Beacons can also be used to estimate distance to the receiver using a concept called the Receiver Signal Strength Indicator (RSSI) [11]. It is the signal strength (in decibels) measured by the receiver (ex. smartphone) when receiving packets from the transmitter (ex. beacon). RSSI reduces as the distance increases, so that we can approximate the distance using the reading. A Beacon's data typically contains a unique ID, Name, Calibrated RSSI at 1m (iBeacon) [10] and Calibrated RSSI at 0m (Eddy stone).

The calibrated RSSI is the expected value of RSSI read by the receiver when it is at the corresponding distance from the beacon. This value is found by actual measurements and then coded into the beacon to transmit. This value is very useful, as explained in the Distance Calculation section.

B. Distance Calculation

In order to calculate the distance between a smartphone and a beacon, an equation needs to be expressed and solved. The following equation from the Android Beacon Library [12] can be used to calculate the distance

$$D = C_1 * RSSI^{C_2} + C_3 \quad (1)$$

The RSSI variable is the received signal strength indicator measured by the smartphone when reading the beacon. The constants C_1, C_2 and C_3 are dependent on the smartphones Bluetooth chip and antenna and can be calculated for a specific device. The equation used in this research is expressed as following

$$D = 0.88290233 * \left(\frac{r}{t}\right)^{4.57459} + 0.045275 \qquad (2)$$

The distance D that is retrieved from the equation 3.2 is the distance from the smartphone to the beacon used in the trilateration calculations.

C. Trilateration

Trilateration is a globally accepted method to calculate the position like triangulation. Angles are essential in triangulation whereas trilateration is deals with measuring distances. This method requires three known access points (APs) and the distance measure from the finder device. As already explained these required distance can be measured by the RSSI value. The exact position of the searching object will be calculated as discussed in [3-5] when the positions and distances has been calculated. This location of the objects will be more accurate when more number of APs are used. If only one access point is available, then the object cannot be find. For example, if the only access point P is known, the object position can be predicted as somewhere on the circle with the center P and the radius is the distance from P to finder object. This technique is also called as proximity-based positioning. The equation describing this circle can be represented as

$$d = (x - x_a)^2 + (y - y_a)^2 \qquad (3)$$

where d is the distance, $\{x_a, y_a\}$ are the coordinates of P and {x, y} are the unknown coordinates of the searched device. Adding the AP Q, it is possible to exclude all but two positions. Since both APs P and Q know their distance to the searched device it is possible to calculate the two points, more particularly the two intersections of the circles. It is also called as bilateration and can be calculated as

$$d_a = (x - x_a)^2 + (y - y_a)^2 \qquad (4)$$
$$d_b = (x - x_b)^2 + (y - y_b)^2 \qquad (5)$$
$$d_c = (x - x_c)^2 + (y - y_c)^2 \qquad (6)$$

where d_a, d_b are the two known distances, $\{x_a, y_a\}$ and $\{x_b, y_b\}$ the known coordinates of P and Q and {x, y} the unknown coordinates. In order to calculate the exact position of the searched device, a third AP R needs to be added. It is then possible to exclude one of the earlier computed intersecting points and thus get a final position. This is done by solving equations 4, 5 and 6. Where the two first equations are the same as in equation 5, referring to P and Q, and the third referring to R. One unique point with coordinates {x, y} which satisfies this system.

Using RSSI values, there is a good chance that the distances are erroneous and could result in non-intersecting circles. The APs could also be placed so that the circles are overlapping without intersecting with each other. Both scenarios would result in an unsolvable equation system. Theoretically, it means that the position cannot be calculated.

III. LITERATURE STUDY

This section discusses earlier researches done in similar areas. The application developed in this thesis is composed of two parts: an IPS system needed to locate the users and a tracking system for locating the lost assets. Works about IPS and examples of tracking systems will therefore be reviewed. As mentioned in the introduction, since our application in based on crowd-sourced localization, meaning that the system needs active users in order to work, related work covering this area will also be reviewed.

A. Indoor Positioning Systems with Bluetooth

Bluetooth can utilize RSSI to be a technique for measuring positions indoors. Sheng Zhou el at. [1] have made such a system where they turned off the automatic transmitter power control to get a novel use of the RSSI. The distance was estimated by transmitting between a mobile receiver and a reference point. They were also using a Line-Of-Sight radio propagation model within a single cell. The ability to navigate indoors using BLE and a smartphone has been studied by Milan Herrera Vargas. The author set up an indoor environment composed of two BLE beacons and a smartphone. He claims that the main purpose of his report was to introduce indoor navigation based on BLE but that this technology is still limited which led to unstable measurements and bad accuracy. The bad accuracy is an interesting aspect of IPS and is a known issue. Silken Feldman et al. have in their scientific paper tried to overcome this problem with and optimization method least square. They got a precision of 2 meters but think it could be even better by using a Kalman Filter. Teng Ge et. al [2] made a comparable research about indoor navigation but focused on making it available for blind people. By using BLE beacons and a smartphone, he developed and compared two different positioning software. The first one, based on triangulation and fingerprinting, gave good a static performance, but was not a reliable navigation system. In the second software a proximity algorithm was instead used, along with a real blind person. This experiment gave on the other hand a better output letting him conclude that a blind person was able to navigate through the route without any help from other people.

B. Other approaches to IPS

Instead of using Bluetooth, other technologies can be used to calculate positions. Examples of such approaches are presented below.

C. Wi-Fi based localization

Wi-Fi based localization is probably the most common technique used for IPS. Behrang Parhizkar et al [3]. discuss such a solution as they try to position a user within a building. Thomas J. Gallagher et al [4]. are also utilizing the Wi-Fi technology as they describe a campus-wide positioning system at the University of New South Wales in Sydney, Australia, and works outdoors as well as indoors.

D. Geomagnetic Technology

Indoor Atlas is an IPS company using the earth's magnetic field in order to calculate positions.

By using the compass which works as a magnetic sensor, it is possible to use the magnetic fields inside a building to accurately pinpoint and track a user's position indoors.

Geomagnetic [5] is the foundation of this technology but together with Wi-Fi and beacons is it possible to develop a hybrid solution in order to reach optimization.

E. Image based localization

Today's smartphones are equipped with many different sensors. Instead of using Bluetooth or Wi-Fi sensors, the smartphones camera can be used for IPS [6]. An augmented reality kind of IPS can be done by comparing pictures taken by the camera with a sample of pictures stored in a database. It is then possible to position the smartphone.

The camera can also be used for visible light communication. This approach uses the emitting light itself, and can provide very good accuracy as well as being free from radio frequencies. These two approaches are however dependent on the line of sight which can be problematic for passive positioning when the smartphone camera is obstructed (in a bag or a pocket).

F. Crowd-sourced localization

Some researches within IPS have begun to explore the concept of crowdsourced localization. This concept is mainly about collecting vital data from the users of such systems. By continuously collecting user data [7]. proposed an IPS solution based on Wi-Fi RSSI data, collected by using the crowd. The positioning method used in their approach is fingerprinting. Fingerprinting is a common method, resulting in good positioning accuracy but requires a lot of data to build the fingerprint database. This is why the motivation for using crowd-sourced data is for simplifying the creation of their fingerprint database. The collected data also helps improving and updating the database after its creation. Anshul Rai et al [8]. developed a system called Zee which is also based on crowd-sourced localization. They investigate a hybrid solution of using both Wi-Fi signals but also a smartphones sensor like the gyroscope and the accelerometer. This data is also collected using the crowd and permits to position the users without knowing their initial location, by looking at the number of steps they have walked, the direction they are facing and the velocity of the walk. Other users that needs to be located can then benefit from the fingerprint database obtained from these previous observations. Jindan Zhu et al [9]. discussed about the main problem with crowd-sourced systems, which is the need of having active users collecting the vital data. The lack of users is the biggest limitation of such systems, and they tried to overcome this problem by combining Wi-Fi fingerprints with signals from BLE beacons. This particular approach of using data from beacons to support the lack of user data, let the authors of this paper improve the quality of their fingerprint database. Their work however showed some weakness for positioning the users, because it requires the users to be immobile in order to get a good accuracy and the calculations requires time and cannot be processed in real time.

G. Problem with the existing system

At the conclusion of the literature studies made, the indoor positing system causes many challenges like location accuracy, availability and stability during the deployment. The location accuracy is the main research area to be focused in indoor positing systems which deals with identification of the location with the minimum of 1.5m accuracy. The availability issue evaluates the capability of the model in terms of time required to identify the position of the object. The stability issue deals with the consistent results when the object is dynamic in nature in the application environment.

Along with all these issues, the deployment of beacons, mobiles or finder, object with dynamic nature causes many issues like bugs, responsiveness etc. As the cause of all these problems will be varied from each application. Some specific environments with false negative cases are: Energy resource limitations and threshold level setup impact the application when a beacon is detected by blinds and causes a "false negative" case. Human object detection with shield by the beacon may also leads "false detection". Also reflective surfaces, glittering metals and glass also can cause "false negative" case in wrong places.

H. Problem Statement

Global positing to find the objects in outdoor has been resolved with better technologies like GPS. But when apply the same in indoor applications, the accuracy of the position is not exact due to weak signal for GPS. This necessitate a new method for indoor application to find the object with high accuracy. In last decade the indoor positioning system for pervasive mobile computing has attracted many researchers interest due to its vast applications. Some of the initial research has been proposed to use specialized sensors and actuators placed inside the building to find the objects or people. These methods are quite accurate but it is not scalable to apply commercial applications and leads to more deployment costs. Another important method for indoor positioning is suggested to use the existing hardware infrastructure through wireless access points to triangulate and localize using mobile devices. This method also provides accurate locations but it requires radio frequency setup throughout the building. This also leads to more deployment cost and time. To overcome all the drawbacks of these olden methods, current research focusing on sensor embedded mobile technologies. But still proper implementation with improved hardware are required to improve the accuracy, availability and stability.

I. Objectives

As mentioned in the problem statement many researchers have been proposed their solution based on BLE and mobile device for indoor positing applications. The main objective of this research work is to analyze those existing models and implemented a new system combining the efficient and easy to deploy techniques to increase the accuracy of the location prediction. Also this research need to bring the state of the art deployment techniques which are adoptable to any indoor applications. This method is aimed to implement the indoor positing system on an android platform by creating an android application. This android application also achieves the mobility in localization.

IV. IBPS: IBEACONS BASED IMPROVED INDOOR POSITIONING SYSTEM

The proposed IPBS model is designed as multi-layer architecture. At the hardware layer beacons plays a major role. In this IBPS model each beacon is configured with different transmission power and physical location. Since this model developed for indoor applications, the higher power energy resource is attached with all the devices. The working flow of this model is deigns with broadcasting. Through the broadcast request every neighbors will be identified by every other beacons. But identifying the required object location will follow iBeacon protocol. For example, Object P may be close to Object Q but it may not be detected by any specific location, while Object Q may be detected with its exact position, this model infer that P is at the same location as Q.

This situation leads to “false-negatives” and it did not deal with reflections and irregularities of antenna patterns. To resolve these type of “false-negative” responses, the proposed improved indoor position system, uses a software filtering layers whose purpose is to consider spatial layout. This reasoning in this layer is based on the time it takes a user to move from a place to another.

A. Overview of the research work

Execution setup of the proposed IBPS model is depicted in figure 1. Also this section describes execution flow as described in figure 2.

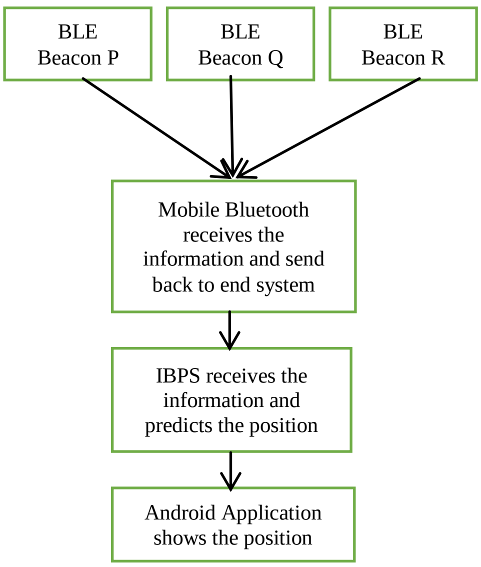

Fig. 1. Deployment of the indoor positing system

B. Approach to Indoor Positioning

Indoor positioning can be generally approached in two ways: precise and zone based. Precise indoor positioning implies identifying the exact user position at all times, with an accuracy of up to one meter. It involves measuring the distance of the user from fixed points nearby, whose positions are pre-known (these fixed points can be beacons in case of BLE, and Wi-Fi Access Points in case of Wi-Fi, etc.), and using trilateration to calculate the user position. Trilateration is also used by GPS for outdoor positioning.

Zone based indoor positioning involves creating multiple zones to cover an indoor location, and then identifying the zone in which the user is currently present. The zones could be as small as 1m x 1m (for example, adjacent to a painting in a museum), or as large as 10m x 10m (for example, a hall). Thus, the zone size could be decided by the administrator during initial setup, depending on the accuracy desired. For BLE, this approach uses the concept of proximity from a beacon, where we classify a user as located Immediate, Near, or Far from a beacon. This gives us an estimate of the user’s position without involving too much computation. Immediate range is usually defined as less than one (or sometimes two) meter(s). Near range is usually between two and six meters. Far range is usually beyond six meters.

BLE Beacons work best with the zone-based approach because the noise in RSSI leads to error-prone distance calculations preventing a precise positioning. In the remainder of this report, we discuss the experiments and results of the zone-based approach.

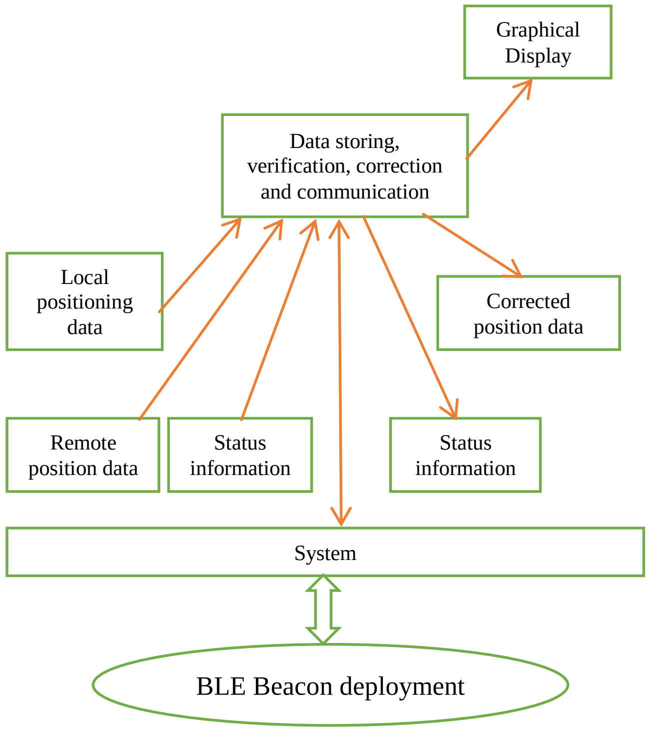

Fig. 2. Overall System Architecture

C. Zone Based Approach and Calibration

In case of the zone-based approach, a system calibration must be done to define the values of Immediate, Near, and Far ranges. For example, the Immediate range could be under a meter, the Near range could be between one and six meters, and the Far range could be beyond six meters. In this case, the user can stand exactly one meter away from the beacon, facing it, and record the RSSI readings on his/ her phone. The mean value of these readings would define the boundary of the Immediate range. Similarly, the mean value of the RSSI readings at six meters, combined with those at one meter, would define the Near range, and likewise the Far range. Once the calibration procedure is complete, the recorded values are stored in a database, which would then be queried at runtime to establish the zone for a given beacon, using the measured RSSI value.

Such an implementation results in gradual boundaries instead of sharp ones, since the RSSI can vary slightly at the edges of the various ranges.

As an example, the Near range could have an upper limit falling between 5 and 7 meters, rather than a crisp 6 meters. This variation is usually acceptable in most scenarios. RSSI values depend on the transmit power, so different beacons with different configurations of transmit power would result in different. RSSI values at the same distance.

Thus, ensure that beacons have the same transmit power before proceeding with calibration. Another important point is that RSSI readings vary from handset to handset, and this is a key problem considering different Android based phones. One way to compensate for this variation is to use a good quality (high sensitivity) phone and calibrate while standing a little further away from the desired range limit. For example, when calibrating for Immediate range to be up to one meter, calibrate while standing at 1.2-1.5 meters. The signal level picked up by a highly sensitive phone at 1.2-1.5 meters can be at the same level as a low sensitive phone at one meter. Similarly, near range could be calibrated at 7 meters instead of 6 meters. This way we can accommodate various handset models.

V. RESULTS

The results are presented in the table below. Here, we can see that the error rate generally stays very low but increases to 25% when the device is close to the wall. This happens because the signals coming from the neighboring room are not diminished sufficiently by the wall to completely distinguish between the two beacons on each side of the wall.

Table- I: Error rates on different positions

Position	1	2	3	4	5
Correct estimates	70%	60%	75%	70%	64%

We started by plotting the RSSI graphs at various distances, using multiple sets of beacons and phones. First, we placed 10 beacons in a grid-based layout in an office space (30m x 30m). Any two beacons had about 6 meters' space between them. These beacons were pasted on the walls or pillars, with a placement height of 2 meters from the floor. We recorded RSSI values for a particular beacon, facing it; with the phone held horizontally at a height of about 1.2 meters from the floor (this scenario imitates a user standing with the phone in his/her hand). The beacon was always at line-of-sight from the phone. We started close to the beacon (1 meter apart) and gradually walked backwards, crossing 5 meters, facing the beacon all the while. For the purpose of this whitepaper, we set the beacons to -12 dBm of transmit power. When varying the transmit power, we observed similar behavioral patterns (higher power leads to higher RSSI). We created a custom app to measure RSSI values, and also used the Beacon Toy app to confirm that our app performed similar to a known app in the field. The result for one such measurement is shown in below. Note that IBeacon mentions that for a beacon transmitting at -12 dBm, the RSSI1m should be -77 dB, the Power Curve Distance Formula Calculation (observation) and the reference graph for which is shown below.

Step 1: Calculate Ratio

Table- II: Measurements of hardware deployment

Distance (m)	**RSSI**	**Ratio**
0.25	-65	1.120689655
0.5	-59	1.017241379
1	-59	1.017241379
2	-52	0.896551724
3	-72	1.24137931
4	-83	1.431034483
5	-86	1.482758621
6	-80	1.379310345
7	-85	1.465517241
8	-89	1.534482759
9	-96	1.655172414

Step 2: prepare regression data

Table- III: Regression Variables for the calculate ratio

Independent	Dependent
1.120689655	0.25
1.017241379	0.5
1.017241379	1
0.896551724	2
1.24137931	3
1.431034483	4
1.482758621	5
1.379310345	6
1.465517241	7
1.534482759	8
1.655172414	9

Step 3: Run regression to get mean A and regression B

Table- IV: Mean and Regression

A	0.882909233	B	4.57459326

Step 4: Test prediction using mean and regression

Table- V: Calculations based on d=A*(r/t) ^B

RSSI	Ratio	Actual Distance	Predicted Distance
-65	1.120689655	0.25	1.486933229
-59	1.017241379	0.5	0.954724179
-59	1.017241379	1	0.954724179

-52	0.896551724	2	0.535756655
-72	1.24137931	3	2.374056029
-83	1.431034483	4	4.549377249
-86	1.482758621	5	5.351725397
-80	1.379310345	6	3.844261058
-85	1.465517241	7	5.072908837
-89	1.534482759	8	6.260609705
-96	1.655172414	9	8.85186673

Step 5: Calculate C

The Optimize 1m accuracy Calculation of C is 0.045275821

Step 6: Test prediction using A, B & C

Table- VI: Calculations based on d=A*(r/t) ^B + C

RSSI	Ratio	Actual Distance	Predicted Distance
-65	1.120689655	0.25	1.53220905
-59	1.017241379	0.5	1
-59	1.017241379	1	1
-52	0.896551724	2	0.581032476
-72	1.24137931	3	2.41933185
-83	1.431034483	4	4.59465307
-86	1.482758621	5	5.397001218
-80	1.379310345	6	3.889536879
-85	1.465517241	7	5.118184658
-89	1.534482759	8	6.305885526
-96	1.655172414	9	8.897142551

In file above, as seen here, a lot of noise is present in the readings, due to which it is hard to know the accurate value. To compensate for this noise, we created a custom low-pass filter with a threshold technique, such that sudden large variations in RSSI were ignored, and gradual small ones were accumulated. The filtered output was then used for our zone-based approach.

VI. CONCLUSION AND FUTURE WORK

The proposed method to find the position of an object or person in an indoor application has been implemented and deployed in an indoor environment. The results have been tabulated and the accuracy of this proposed model has proved that the combination of BLE, iBeacon and Android application is an efficient way than the existing model. Also this model deployment cost is cheaper than the existing model. The successful development of this indoor positing system may be helpful in various applications. As a future enhancement, the performance of the positioning system can be further improved using algorithms namely Extended Kalman Filter and Unscented Kalman Filter and Accuracy of the position system may be still improved by the appropriate deployment and proper number of fixed wireless receivers.

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