

Bluetooth Low Energy based Indoor Positioning on iOS platform

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Abstract—In this age of IoT (Internet of Things), Indoor Positioning (IPS) is considered as one of the most popular topics and has been researched widely all around the world, as the result of various applications it can provide. However, IPS is also a challenging topic that has a number of stringent requirements, such as cost, energy efficiency, availability and accuracy. The development of Bluetooth Low Energy (BLE) iBeacon has opened great opportunities for researchers to solve those challenges. In this paper, we present our iBeacon based positioning system, which we built as an application running on iOS platform. We also present Fingerprinting – the main positioning technique used in our system, in which we configure its fingerprints to improve accuracy. With that, a machine learning algorithm called k-Nearest Neighbor (kNN) is applied to extract the most probable user location. In addition, we also use Kalman Filter in order to enhance the stability of iBeacon’s signal. Our system results in a 60% – 71.4% accuracy rate and an error of up to 1.6 m, which is acceptable in IPS.

Index Terms—Indoor Positioning, Bluetooth Low Energy, Apple’s iBeacon, iOS, Fingerprinting, k-Nearest Neighbor, Kalman Filter.

I. INTRODUCTION

Indoor positioning is the process of obtaining a device or a user location in an indoor setting or environment [1]. In the last few decades, it has been researched and applied in a variety of aspects, such as robot navigation, indoor location tracking, disaster management, health-care, and other indoor location based services.

A number of methods including Wi-Fi, Radio Frequency Identification Device (RFID), Ultra Wideband (UWB) and ultrasound, etc. have been applied in order to implement indoor localization. However, these techniques do not quite meet the requirements of IPS, as they either highly consume power, require high cost and complex extra hardware, or provide low accuracy [1] [2].

In 2013, Apple Inc. introduced iBeacon – a small, battery powered, wireless device that uses Bluetooth Low Energy (BLE) technology to send its advertisement to compatible smartphones or tablets within its proximity [3]. By using iBeacon technology together with iOS platform, developers can create proximity based applications that can be used in public indoor places, such as shopping malls and museums. The development of BLE iBeacon also brings new opportunities to indoor positioning, as it is simple to deploy, energy efficient and can provide better accuracy with lower cost.

Following the development of BLE iBeacon technology, there have been a wide range of methods and algorithms studied by researchers around the world to implement BLE based indoor positioning. The most popular method is received signal strength indicator (RSSI) based, which can be divided into 2 main approaches: triangulation and fingerprinting. In this paper, we built a system using fingerprinting. This method requires building an offline radio map for the interested indoor area. That can be done by collecting and storing beacons RSSI data at different location points of that area. There have been several studies focusing on using BLE based fingerprinting.

Zhang et al. [9] compared 3 algorithms that are usually applied with Bluetooth based fingerprinting. This included kNN, Neural Networks and Support Vector Machines. The authors proved that kNN was the better candidate for real-life localization compared to the other two.

The work of Kajioka et al. [11] is among the first studies that apply fingerprinting with BLE beacons. The authors installed 22 beacons inside and outside a room and then gathered beacons data at 56 observation points. The data for each point contained that points ID, beacons ID and their corresponding RSSI. A Google Nexus tablet was used to collect and send these data to database/estimation server via wireless LAN. Finally, a Sum of Squared Difference (SSD) algorithm was then applied for matching the current location point with the observation points.

Faragher and Harle study [12] investigated a number of key factors for accurate positioning with BLE and fingerprinting. This comprised fading mitigation method, its window selection, beacon advertising period, beacon density, beacon transmitting power and fingerprinting dimensionality. At the end, the authors showed that BLE based fingerprinting resulted in a significant improvement compared with Wi-Fi based fingerprinting.

In the work of Peng et al. [13], a detailed description on constructing offline fingerprinting database was included. In the online phase, instead of the conventional kNN, the authors proposed an enhanced algorithm comprising Similarity Improved kNN and Weighted kNN. This new method is called Iterative Weighted kNN (IW-kNN). The study’s experimental results showed that IW-kNN outperform the conventional one. Wang et al. [14] also proposed an improved kNN algorithm called Euclidean Distance Correction in their study.

Zhuang et al. [15] showed that signals and noises in RSSI measurements from 3 channels of the BLE band can be different. Because of this, the authors generated separate radio map database of each channel for fingerprinting. Another work also applied separate-channel fingerprinting is from Ishida et al. [16]. In their study, fingerprints from each channel contributed to build a big offline database. Wen et al. [17] developed an algorithm called Dynamic RSS feedback to characterize the indoor environment.

Most of the mentioned studies include methods to reduce the instability of beacons RSSI, which is the main issue of fingerprinting. In order to overcome this problem, our work applies Kalman Filter.

In this paper, we propose an indoor positioning system, in which our main approach is fingerprinting. In this technique, we configure the offline data in order to enhance the positioning accuracy. A machine learning algorithm called k-Nearest Neighbor (kNN) is used to decide the user location. Also, as mentioned above, to tackle the RSSI problem of fingerprinting, we include a Kalman Filter. To test the performance of the system, we build an application running on iOS devices that returns the users current position on the screen.

The paper is structured as follows: Section II introduces Apple's iBeacon and an overview of our positioning system. In section III, the positioning methodology used in the system which includes Kalman Filtering, Fingerprinting and kNN is described. In section IV, we discuss about our experiments and their results. Section V concludes our paper.

II. BLE iBEACON AND INDOOR POSITIONING

A. BLE iBeacon

1) *Characteristics of iBeacon*: An iBeacon's advertisement includes 3 following components, which provide the identifying information for that beacon [4]:

- Universally Unique Identifier (UUID): a 16-byte value.
- Major: a 2-byte value.
- Minor: a 2-byte value.

Hierarchically, the UUID value can be used to differentiate an organization's beacon from others, the major value is used to specify a small group of beacons, and the minor value is for identifying a particular beacon [5]. After each amount of time called advertising interval, the beacon send its advertisement to the nearby mobile devices via BLE.

Originally, iBeacon is developed for proximity based services [6]. Once the user device receives the advertisement of a beacon, the application running on the device can identify that the user is in the proximity of that beacon. The application can then display on the device's screen the corresponding information related to the area where the beacon is placed.

2) *iBeacon and iOS platform*: Apple provides a framework called CoreLocation for iOS application development [4] [5]. By using this, developers can build different applications to provide proximity based services with beacons on iOS devices.

B. Overview of our indoor positioning system

As mentioned above, our positioning system is based on RSSI, or the strength of the received signal at user device. The value of RSSI from a beacon varies as the user changes his/her location. The closer the user is towards the beacon, the stronger the RSSI from that beacon is. Making use of this, we apply Fingerprinting – a technique relevant to RSSI [1], in which we collect and store RSSI data at different points on an indoor location, and later on with kNN algorithm, use those stored data to compare with the RSSI data received by the user device in real time, to decide his/her location [1] [2].

Fingerprinting technique is cost efficient and simple to implement. However, RSSI values are often unstable due to the indoor environment and can be severely affected by a number of factors, such as multipath fading and indoor noises [1] [2], which therefore can lower the accuracy of fingerprinting. So as to reduce the fluctuation of RSSI and improve positioning accuracy, we apply Kalman Filtering – a method proposed by R. E. Kalman in 1960 [7], which has now become a standard approach for optimal estimation [8].

In our system, RSSI values from beacons received at the user device are forwarded to Kalman Filter. The smoothed RSSI values are then compared with the data collected in the first stage of fingerprinting using kNN, to estimate the user location and display it on the device screen. Figure 1 shows a clearer view of how our system works.

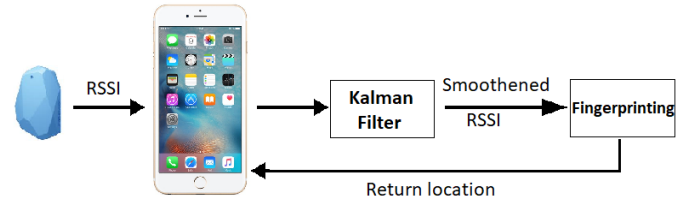


Fig. 1. Overview of the proposed system.

III. POSITIONING METHODOLOGY

In this section, we introduce Kalman Filter, Fingerprinting and k-Nearest Neighbor – 3 techniques used in our system.

A. Kalman Filter

Kalman Filter is a linear optimal state estimation method which uses the following state model [8]:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_k \quad (1)$$

$$z_k = Hx_k + v_k \quad (2)$$

In this model, the state x_k , which is the RSSI value to be estimated in our case at time k , is a function of the previous state at time $k - 1$, the control signal u_{k-1} and the process noise w_k . The measurement z_k , which is the observed RSSI value from a beacon at time k , is a function of the state at time k and the measurement noise v_k . A and B in Equation 1 are called state transition matrices, H is called the observation

matrix. In our case, w_k and v_k are assumed as zero mean Gaussian white noises, or more specifically, $w_k \sim N(0, Q)$ and $v_k \sim N(0, R)$.

There are 2 stages in Kalman Filter: the time update (prediction) stage and the measurement update (correction) stage.

- Time update:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k \quad (3)$$

$$P_k^- = AP_{k-1}A^T + Q \quad (4)$$

- Measurement update:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \quad (5)$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \quad (6)$$

$$P_k = (1 - K_k H)P_k^- \quad (7)$$

In these formulas, \hat{x}_k^- is the prior estimate at time k , which in a way, means the rough estimate before the measurement update correction. P_k^- is the prior error covariance. K_k is the Kalman gain. \hat{x}_k is the posterior estimate at time k , which is the smoothed RSSI values in our case. P_k is the posterior error covariance.

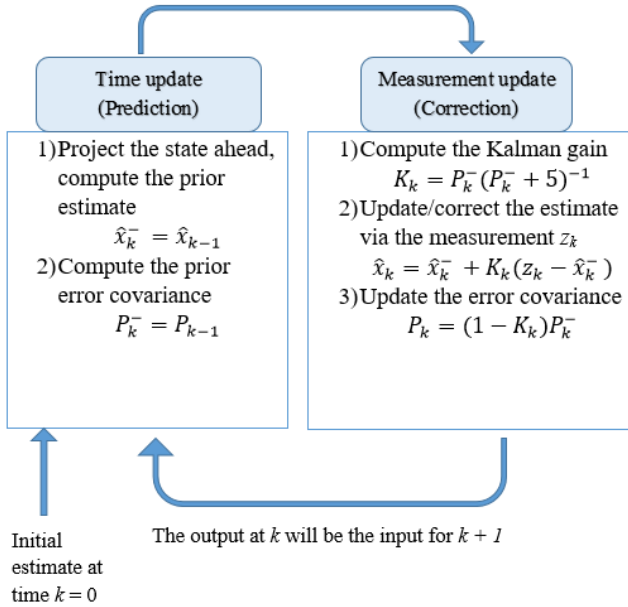


Fig. 2. Working process of applied Kalman Filter.

In our study, we use a one-dimensional Kalman Filter in order to smoothen RSSI values observed at fixed location points, i.e., Kalman Filter is used to smoothen RSSI values observed when we stand still at each of those points. Because of this, there is no control signal u_k . Also, because the RSSI values from a beacon at time $k-1$ and k at a same location point should be the same, we let A equal to 1. We choose H to be 1, as we know that an observed RSSI value is composed

of the state RSSI value and the measurement noise, as in Equation 2. Parameters Q , R and the initial value of P used in our system are obtained from doing experiments, and are given as follows: $R = 5$, $Q = 0$, $P = 10$. The final time update and measurement update are shown in Figure 2

B. Fingerprinting and k-Nearest Neighbor

Fingerprinting is a prior scene analysis based technique which include 2 stages [1] [2] [9]:

- Offline stage: In this stage, signal measurements, or the RSSI values in our case, are collected at different location points on the indoor area where the positioning system to be used. Each location has a different set of RSSI measurements from the beacons, each set is called a fingerprint. The fingerprints are then stored in the database.
- Online stage: Once the positioning system is deployed, the online measurements, or the current RSSI values observed in real time, are compared with the offline measurements, i.e, fingerprints to estimate the user location.

In the second stage of fingerprinting, to compare the online observed data with the one stored in the database, we use an algorithm called k-Nearest Neighbor – a machine learning method which has been widely applied in indoor positioning [10]. The idea of kNN is that for each user location, it computes the distance between online data observed by the user and every fingerprint recorded in the database, and then return k locations that have the corresponding fingerprint with smallest distances [9]. In our case, k is 1. Assuming that the signal measurements data of the user location is $V_a = (v_1, v_2, \dots, v_m)$, in which v_j ($j = 1, 2, \dots, m$) is the observed signal measurement from the j^{th} beacon. These data are then compared with the fingerprint data by calculating the following Euclidean distance:

$$d(V_a, V_i) = \sqrt{\sum_{j=1}^m |v_j - v_{ij}|^2} \quad (8)$$

In which: $V_i = (v_{i1}, v_{i2}, \dots, v_{im})$ is the i^{th} fingerprint data stored in the database. v_{ij} ($j = 1, 2, \dots, m$) is the offline signal measurement from the j^{th} beacon.

After that, the location corresponding to the fingerprint data that has the smallest value of d is chosen to be the user location. In order to improve the accuracy of the system, instead of using only RSSI values from the beacons as a fingerprint, we configure the fingerprint for a location point as follows:

$$\text{Location} = (x, y) = [\text{Nearest Beacon's Major}, \text{RSSI}[0], \text{RSSI}[1], \dots, \text{RSSI}[n-1]]$$

In which: $\text{RSSI}[0], \text{RSSI}[1], \dots, \text{RSSI}[n-1]$ are RSSI values of n nearest beacons whose values are in descending order. *Nearest iBeacon's Major* is the major of the beacon that has the RSSI value of $\text{RSSI}[0]$.

Using this kind of fingerprint, we mostly base on the major and the RSSI value of the nearest beacon (which are *Nearest*

iBeacon's Major and RSSI[0]) to compare the online measurements with the ones in the database. As the RSSI value of this beacon is the strongest and the most reliable compared to the further beacons, using it to decide user location is likely to provide higher accuracy.

C. Proposed system workflow

Figure 3 shows the workflow of our indoor positioning system. After the beacons send signal to the user device, if n or more beacons are found nearby the user, the system then chooses n beacons that have strongest RSSI values. These values are smoothened by Kalman Filter, before being compared with fingerprints in the database using kNN to extract the most probable user location.

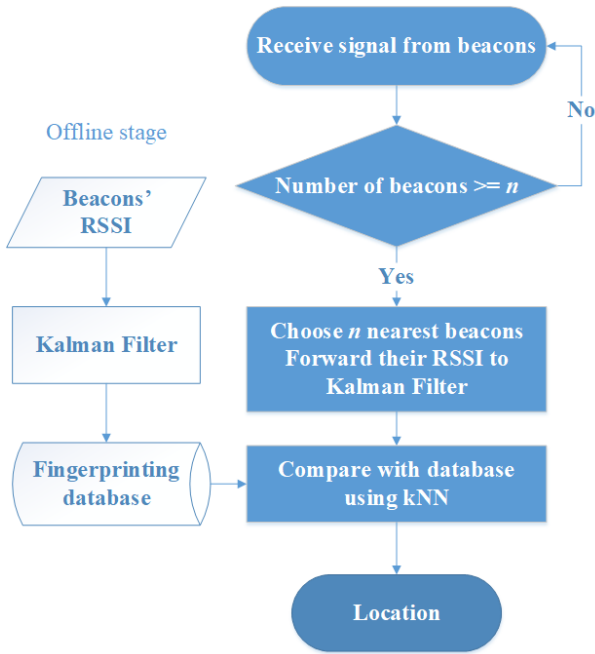


Fig. 3. Proposed system workflow.

An example of the workflow is illustrated in Figure 4. Three BLE beacons are deployed in this example. Their majors are 36616, 7503 and 64882, respectively. In the offline phase, the beacons' RSSI values are filtered by Kalman Filter. The data for each location points are then stored in the database. In the online phase, the user receives data from the beacons. As the system detects that the number of nearby beacons is equal to 3, their RSSI are filtered. We then achieve an online data vector as shown in Figure 4. After that, the Euclidean distance between this vector and each of the offline vectors in the database is computed using Equation 8. In this example, location 1's data vector results in the smallest distance. Therefore, location 1 is chosen to be the user current position.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we show our experimental results. To evaluate the accuracy of our indoor positioning system, we

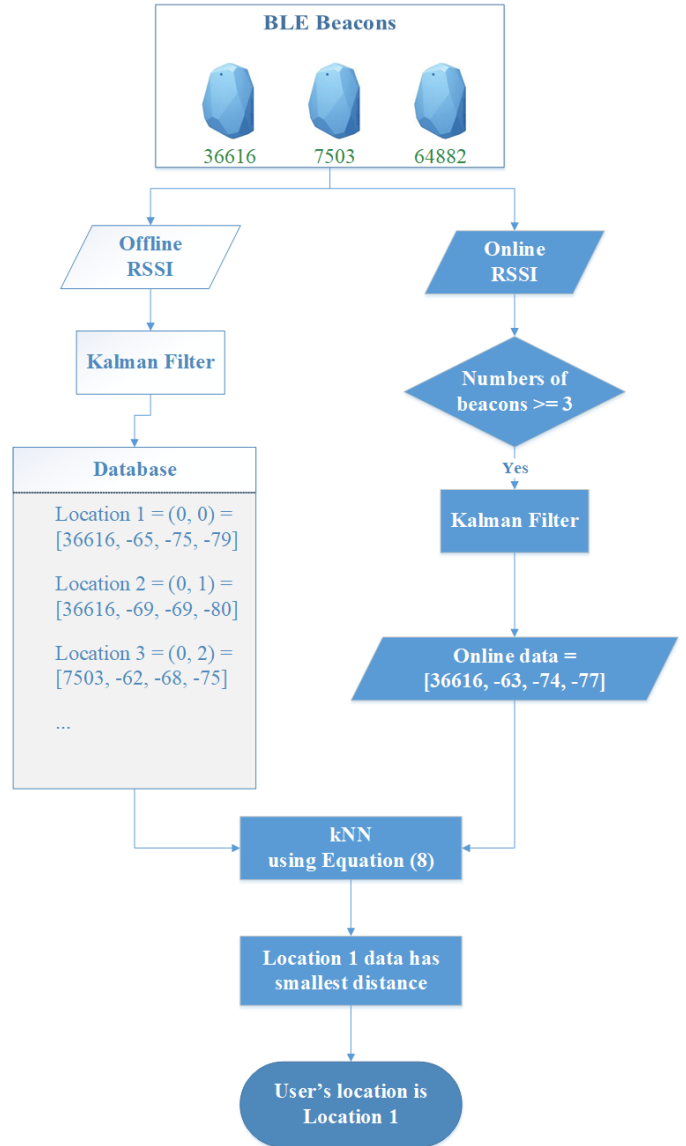


Fig. 4. Example of the workflow.

built an application running on iPhone 5S and implemented 2 experiments, which were done on the first floor of one of our university's buildings. The deployed area was 14 m x 5.5 m. Table I summarizes the equipments related information used in both of our experiments. The number of beacons used in each of them were 3 and 4, respectively, with 2 different ways of placing them.

A. Experiment 1: Using 3 beacons

1) *Experiment set-up:* In this experiment, we placed 3 Estimote beacons in 3 positions, with the distance between 2 beacons of 6 m. In the offline stage of fingerprinting, we collected RSSI values from the 3 beacons at 21 location points on the first floor of the building, each point was assigned with coordinates. The distance between 2 neighboring points was

TABLE I
SUMMARY OF DEVICES PARAMETERS

User Device	iPhone 5S
Wireless Interface	BLE v4.2/ 2.4 GHz
Operating System	iOS 11.2.6
Beacons	Estimote iBeacons
Broadcasting Range	50 m
Advertising Interval	100 ms
Broadcasting Power	0 dBm (Strong)
Major	Yes
Minor	Yes

1.6 m. The set-up of this experiment is illustrated in Figure 5.

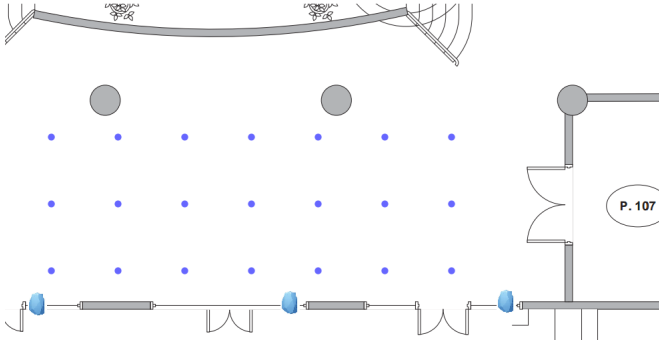


Fig. 5. Experiment 1 set-up.

After that, we registered the data corresponding to 21 location points into our application's database. An example of a point's data can be viewed as follows:

$$\text{Location 1} = (x : 0, y : 0) = [36616, -65, -75, -79]$$

Then, as we walked through the location points, the application tracked our position and displayed it on the phone screen. Figure 6 shows a screenshot from our application.

In order to show the influence of Kalman Filter on our system, we carried out this experiment in 2 following cases: one with our system with Kalman Filter, Fingerprinting and kNN, as we mentioned in section II and III; and the other one with the same system, but without Kalman Filter.

2) *The system without Kalman Filter*: The result of this case is shown in Figure 7, as the red line indicates our true walking path, and the blue dashed line indicates the path tracked by the application.

Without Kalman Filter, the system resulted in a low accuracy rate of 20% with the error up to 3.6 m. The average error was 2.23 m. The locations that the application returned on the device screen was also unstable. This is due to the instability of RSSI caused by the indoor environment.

3) *The system with Kalman Filter*: Figure 8 shows the result for this case. Our system with both Kalman Filter, Fingerprinting and kNN correctly tracked 60% of the location points with the error between 0 – 1.6 m. The average error was 0.71 m. The results returned by the application was also more stable. The remaining 40% of points that were inaccurately

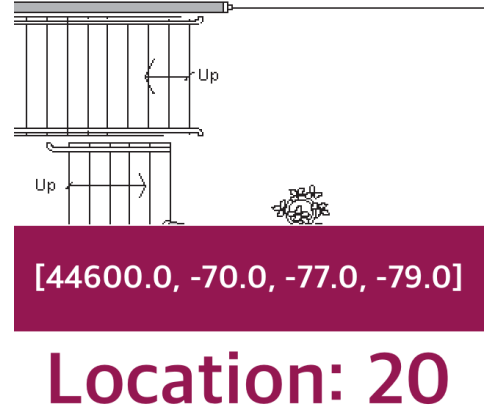
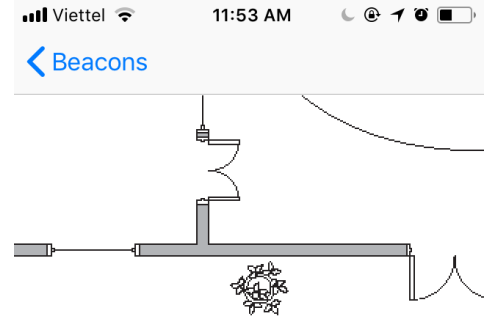


Fig. 6. Screenshot of the application.

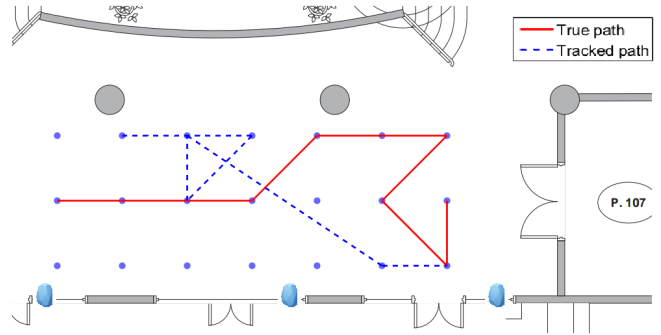


Fig. 7. Result of the system without Kalman Filter.

tracked were still due to the RSSI values being affected by the indoor environment. However, this result showed great improvement in term of accuracy and stability compared to the system without Kalman Filter.

B. Experiment 2: Using 4 beacons

1) *Experiment set-up*: Similar to experiment 1, we collected and stored data from 21 location points. The difference in this experiment compared to the previous one was the use of 4 beacons, which were placed as described in Figure 9.

In addition, we included in our walking path 6 location points whose offline data were not stored in the database. These were named G1 to G6, which is shown in Figure 10.

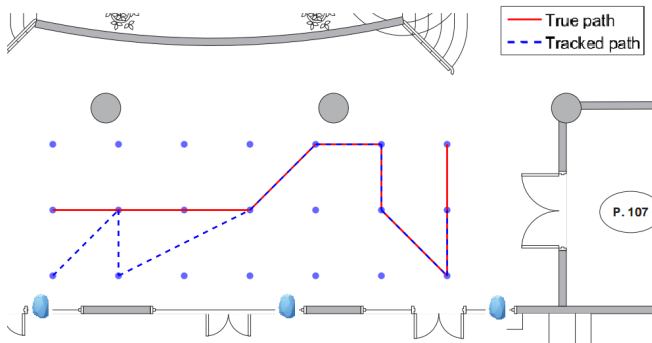


Fig. 8. Result of the system with Kalman Filter.

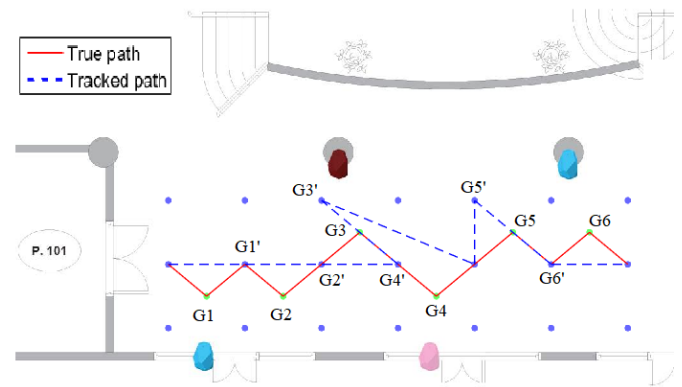


Fig. 10. Experiment 2 result.

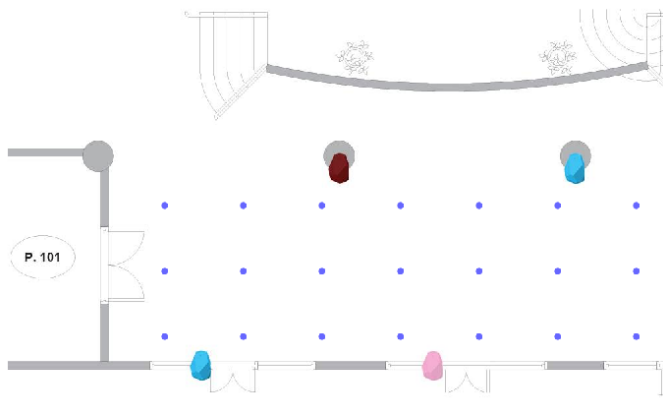


Fig. 9. Experiment 2 set-up.

2) *Results:* In tracking the points included in the database, the system resulted in 71.4% accuracy, an error of 0 – 1.6 m with the average of 0.32 m. For the points that were not stored, i.e., G1 to G6, the location returned were the stored points that were nearest to them, which we named G1' to G6' in Figure 10. Thus, the overall average error in this experiment was calculated to be 0.77 m.

These results show that by increasing the number of beacons used and changing how they are placed, the positioning accuracy can be improved.

V. CONCLUSION

In this paper, we have introduced our BLE iBeacon based indoor positioning system, which we built as an application running on the iOS platform. The system used Kalman Filter in order to reduce the fluctuation of RSSI, and this showed good results in improving the stability of both RSSI and the system. Fingerprinting and k-Nearest Neighbor method was also applied with our configured fingerprint to improve positioning reliability. In tracking a user location, our system resulted in a 60% accuracy rate in the case of using 3 beacons, and 71.4% in using 4 beacons, with an error of up to 1.6 m for both cases. In the future, we plan to study and apply a motion model with the use of smartphone's internal sensors to track the user location while he/she is moving.

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