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Indoor Positioning System Using Combination of Trilateration and Fingerprinting Methods

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ABSTRACT

Positioning technology continues to develop. Positioning which is widely used and can work very well outdoors is to use GPS (Global Positioning System). However, GPS cannot run well indoors because of many obstacles in a building. The study was conducted with the topic "indoor positioning system". This research using BLE (Bluetooth Low Energy) technology because it consumes the least energy and can last a very long time. The focus of this research is to use a combination of trilateration and fingerprinting methods to improve accuracy performance. The first stage determines the reference point and forms a radio map. The second stage consists of estimation using the trilateration method. The log distance path loss model/Log-normal shadowing model was used for the propagation model. The evaluation of the proposed method is in a room with a size of 21m x 12 m, 100 sample data for each reference point, and 10 sample data for each test point. Error performance is evaluated using average error, min error, max error, median and 90th percentile. The results of this study if compared with results that only use the trilateration method show that the proposed hybrid method has better accuracy performance and fewer errors rate.

Key words: Fingerprinting, Hybrid Method, Log Distance Path Loss Model, Log Normal Shadowing Model, Trilateration.

1. INTRODUCTION

Positioning is commonly used is GPS (Global Positioning System) technology that is well known. It has a good level of accuracy when used outdoors. With a more sophisticated level of GPS development, the GNSS (Global Navigation Satellite System), the accuracy can reach up to the millimeter level [1]. The technology used by satellites has disadvantages if used indoors. The disadvantage is when the satellite signal is obstructed by obstacles in the building, causing a low level of accuracy.

It required technology that can determine the position of objects that are in a room. Research on the "Indoor Positioning System" continues to grow with a variety of methods and technologies used [2]. Each method and technology have advantages and disadvantages, allowing different approaches such as a combination of technology to be used for positioning [3]. The survey was also conducted from various perspectives such as energy, efficiency, availability, cost, range, latency, scalability, and accuracy [4]. And it is also predicted that after the rise of IoT (Internet of Things) technology, a technology that can support or collaborate with IoT is a technology that will continue to develop in the future.

The first stage of the proposed hybrid method is the placement of the BLE position in the testing room. The X and Y positions of BLE Position, reference point, and test point must be recorded. Taking sample data for each point. The fingerprinting phase will make a radio map database. The second stage will be an estimation of distance using the propagation model and last using trilateration as an estimation point.

An evaluation needed to prove that the proposed method has better performance. Error performance will be calculated and compared to the performance of trilateration only method. The results of the evaluation can be drawn a conclusion regarding the proposed combination method.

2. RELATED WORKS

There are various methods used in various studies regarding indoor positioning systems [3], [4], [5]. Regarding comparison and indoor positioning survey which discusses the technology, techniques, and algorithms used. The performance of research concerns is accuracy, availability, coverage area, scalability, cost, and privacy. There are several technologies used and continue to develop today such as Radio Frequency Identification (RFID), Ultra-Wideband (UWB), Infrared (IR), Ultrasonic, ZigBee, Wireless Local Area Network (WLAN), Cellular Based, Bluetooth, and Image-Based. There are several techniques for indoor positioning systems including triangulation, fingerprinting, trilateration, proximity, and vision analysis. Also needed is an appropriate mathematical algorithm [4]. Each technology, technique, and algorithm used has advantages and disadvantages depending on the performance of what you want to be the focus of research [6]. There is still much to be faced in this research topic, especially in the field of precision accuracy, it is possible to use hybrid or combination technology to improve the performance of the indoor positioning system.

The evolution of the Indoor Positioning System explains that various methods and technologies have been used to improve accuracy. State-of-the-art technology used is a technology that uses radiofrequency such as WIFI and Bluetooth because both technologies are now widely used, very common everywhere and the technology continues to develop [2]. [7] provides detail explanation about Bluetooth Low Energy (BLE), technical BLE specifications as shown in Table 1, protocol stacks, and working modes. It also explains the indoor positioning technique using BLE mostly used which is trilateration and fingerprinting.

Table 1: BLE Technical Specification [7]

Frequency Band	2400-2483.5 MHz
Distance/Range	<100m (330ft)
Nominal Data Rate	1 Mbps
Modulation (Technique/Scheme)	AFH/GFSK
Channels (Number/Bandwidth)	40/2MHz
Latency	<6ms
Peak/Average current	<15mA/~µA
Accuracy	1-2m
Security	128-bit AES

Comparison of the two technologies that use radio frequencies is described in [8]. It indicates WIFI has a wider area signal range and the signal is not easily lost. Accuracy test using BLE with the lowest transmit power of -23 dBm shows that BLE is very good for indoor positioning systems because the power used is very low, can last a long time, and installation is very easy. Comparison between WIFI 802.15.4 Low-Rate Wireless Personal Area Networks (LR-WPANs) with BLE [9]. Achieve a Conclusion that both technologies suitable for different applications and will continue to develop. In experiments conducted BLE excels in latency and energy used. Various application scenarios and alternatives in the use of positioning such as navigation, localization, tracking, occupancy, and social interaction [10].

An example of BLE implementation is [11] who use BLE for surveillance of Alzheimer's patients because patients need special attention and the inability to remember things. A proposed patient surveillance notification system uses technology beacons to prevent patient disappearance. This system can provide notification to nurses when the patient has exceeded a predetermined distance threshold.

2.1 Fingerprinting Method

Analyzing the accuracy of BLE [12]. Using fingerprinting techniques that are state-of-the-art. RSSI as a parameter has a lot of fluctuations due to environmental factors, interference, the number of people, and others. Low bandwidth on BLE makes it more susceptible to lost signal. More in-depth research about fingerprinting using BLE [13]. WIFI and BLE use the same radio frequency technology, so it should be noted that they don't interfere with each other.

Another improvement of the fingerprinting technique is [14] combined with the Optimal Transport Model Wasserstein Distance. [15] Fingerprinting with the Sum of Squared Difference (SSD). Using K-Nearest Neighbors (KNN) [16], [17], [18]. KNN, Euclidean Distance algorithm, and Weighted Centroid Localization (WCL) method [19].

Another approach using Machine Learning, Random Forest Algorithm, Support Vector Machine (SVM), and Bayesian Networks [20]. Inverse Fingerprinting (Inv-FP) and Pedestrian Dead Reckoning (PDR) [21]. Particle Filtering [22]. Cell of Origin (CoO) algorithm and Kalman Filter [23]. Kalman Filter with Channel-Separate Polynomial Regression Model (PRM), Channel-Separate Fingerprinting, Outlier Detection, and Extended Kalman Filter (EKF) [24].

Indoor localization using Iterative Weighted KNN (IW-KNN) is proposed [25]. Weighted Centroid Localization (WCL) method reduces the reference point so as to minimize the time required so that it becomes more optimal [26]. Using the window size and the Cramér-Rao lower bound (CRLB). For smoothing the Weighted Fingerprint Construction (WFC) method and the K Nearest Neighbor (KNN) algorithm is used as a classifier [27].

2.2 Trilateration Method

Trilateration is used by calculating the received signal strength indicator (RSSI) [28]. The resulting accuracy is relatively low because the Bluetooth signal received tends to be volatile and unstable. Many factors affect Bluetooth signals. Developed using the Arduino board and mobile application on android [29]. Trilateration is used for determining position estimation as shown in Figure 1. BLE placement approximately a minimum of devices can be read by 3 beacons.

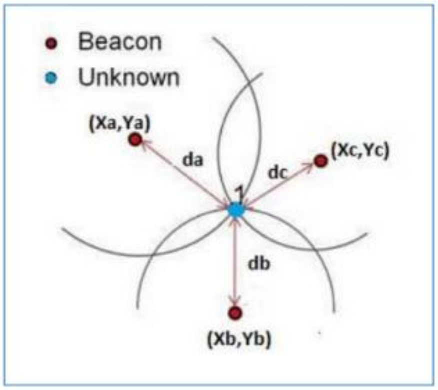

Figure 1: Trilateration for Position Estimation

Calibration is proposed for initialization. RSSI signals collected will be pre-processed to get more stable results. The second step is estimating the distance from RSSI that has been processed and has been calibrated. The final stage is position estimation [30]. Data from the results of the previous process will be used at this stage using improved least square estimation and then evaluated by the trilateration-centroid technique. Least square estimation is used to determine location position in 2D. The propagation model and factor calibration which is commonly used in indoor propagation models is log-normal shadowing. Distance estimation is the distance between beacons and devices that can be known using log-normal shadowing and calibrated factors. Furthermore, the positioning technique uses trilateration-centroid, trilateration will estimate the position of the device from a minimum of 3 beacons.

BLE with channel diversity uses weighted trilateration and Kalman filter [31]. The RSSI value is very important but always fluctuating because of the nature of the signal itself and the effect of multipath, causing accuracy to be less good. To overcome this problem, it is proposed to increase accuracy while reducing power consumption and cost. The three things proposed are frequency diversity, Kalman filtering, and trilateration, this method is called "weighted trilateration". Presenting a system that can track mobile devices and help find their location within building boundaries [32]. With the help of BLE beacons that can be used in different locations. The position of the cellular device can be estimated using the RSSI technique and trilateration method. The whole system is controlled using the MQTT protocol.

2.3 Hybrid Method

Hybrid fusing sliding-window filtering, trilateration, dead reckoning, and Kalman filtering methods to improve the performance of BLE indoor positioning [33]. RSSI smoothing method is used for position calculation with triangulation. The BLE propagation model is used when the distance to the BLE beacon continues to move away and the environment will also have a propagation effect, where RSSI is affected by multipath and fading phenomena. The triangulation method uses 3 beacons as a reference which will form a circle with a certain radius according to the receiver and then the circles will intersect each other. Pedestrian dead reckoning (PDR) algorithm is used to determine the position with a combination of using sensors in mobile devices such as accelerometer, magnetic sensor, and gyroscope with inertia measurement to determine location with a formula. An accelerometer on a mobile device can also be used to detect steps.

Study the path loss model and analyze to choose the best model [34]. There are also using mathematical techniques for positioning beacons. In this study using the indoor path loss model to measure distances using trilateration techniques. There are several models used such as the log distance path loss model and the International Telecommunication Union (ITU) indoor propagation model. The indoor positioning system uses the mathematical technique of linear least squares method and non-linear least-squares method. Fingerprinting technique with calibration technique consisting of point calibration, environment calibration, and point calibration based on proximity.

Hybrid technique for determining location. Triangulation is applied to calculate user positions based on RSSI and fingerprinting methods are used to improve the accuracy and stability of indoor positions [35]. Machine learning is also used with several algorithms to evaluate position predictions. Uses client-server architecture to reduce the computational burden on the user's device. It can also make the indoor positioning system more stable and other diverse service installations can be done on the server.

A number of efforts continue to be made in improving accuracy. [36] Proposed a method of positioning using fusing trilateration and dead reckoning. The Kalman filter is used as a position fusion algorithm. Context information about the environment is also considered to improve accuracy and can result in an improved position. The testing phase is carried out with three approaches: trilateration, dead reckoning, and fusion method.

BLE signal strength with other sensor combinations to support the estimation process using the "constrained extended Kalman Filter" algorithm [37]. The position determination is combined with other sensors, namely: BLE, magnetic field, rate-gyro, and optical flow sensor. Rate-gyro sensor (angular velocity) and optical flow sensor (linear velocity) are used as proprioceptive sensors. It can be used for Pedestrian Dead Reckoning (PDR). Exteroceptive sensors use BLE and magnetic fields. [38] Presents a new scheme that is investigated to increase the computing power of calculations. With a hybrid trilateration technique and fingerprinting approach with Bluetooth low energy. The proposed scheme can guarantee the user's smartphone can estimate the position in the room with efficient calculations with minimal energy resources.

[39] Uses a new hybrid location positioning technique by utilizing inexpensive smartphones and Bluetooth Low Energy (BLE) tags without other infrastructure. The proposed method supports centimeter range positioning accuracy. To ensure high accuracy, the positioning system uses a multilateration algorithm where only time synchronization between audio receivers is required.

3. BACKGROUND THEORIES

3.1 Log Distance Path Loss Model

Various path-loss models can be used. Analysis of various studies shows that the model that is widely used is the log distance path loss model.

$$[P_L(d)]dB = [P_L(d_0)]dB + 10\,n\,log_{10}(\frac{d}{d_0}) + X \qquad (1)$$

The explanation is as follows. $[P_L(d)]dB$ is the value of path loss at distance d in units of dB. $[P_L(d_0)]dB$ is the path loss at distance d_0 in dB units as well. d is the estimated distance that needs to be known in this study. This d distance will be calculated to find out the estimated position of the receiver from the transmitter. d_0 is the exact distance through measurements used as a reference distance to determine the estimated distance to d. n is the path loss exponent that can be tuned according to the environment as summarized in Table 2. Whereas X is a zero-mean Gaussian distributed random variable that is only used if there is a shadowing effect.

Table 2: Path Loss Exponent for Various Environment

Environment	Path Loss Exponent (n)
Free Space	2
Urban Area Cellular Radio	2.7 to 3.5
Shadowed Urban Cellular Radio	3 to 5
Inside a Building – Line –of-Sight	1.6 to 1.8
Obstructed in Building	4 to 6
Obstructed in Factory	2 to 3

Path loss, by definition, is a reduction in the power of electromagnetic waves when propagating or can be said to be the power needed to propagate. Equation (1) can be adjusted according to RSSI value:

$$RSSI = RSSI_0 + 10\,n\,log_{10}(\frac{d}{d_0}) + X \qquad (2)$$

Calculation of path loss is important for the analysis and design of telecommunications system coverage. Path loss is heavily influenced by several factors such as refraction, diffraction, reflection, absorption, surrounding environment, and the distance.

3.2 Euclidean Distance

To find out the distance between 2 points can be determined by using Euclidean Distance as follow:

$$d(p,q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \ldots + (q_n - p_n)^2} \qquad (3)$$

3.3 Trilateration Algorithm

Trilateration is used to estimate the actual position of the test point by calculating the distance from the transmitter. A minimum of 3 transmitters is required to determine position in 2D. The explanation is that x_1y_1 is beacon 1, x_2y_2 is beacon 2 and x_3y_3 is beacon 3. With trilateration it will get the estimated distance of r_1, r_2 and r_3. The three equations for the three circles are as follows:

$$\begin{aligned}(x - x_1)^2 + (y - y_1)^2 &= r\frac{2}{1}\\(x - x_2)^2 + (y - y_2)^2 &= r\frac{2}{2}\\(x - x_3)^2 + (y - y_3)^2 &= r\frac{2}{3}\end{aligned} \qquad (4)$$

4. PROPOSED INDOOR POSITIONING SYSTEM USING COMBINATION OF TRILATERATION AND FINGERPRINTING METHODS

Systematically, the proposed method with a combination of fingerprinting and trilateration is as follows: data averaging, BLE selection, reference point selection, distance estimation, find radius, and the last is trilateration.

4.1 Data Averaging

RSSI dataset that has been collected. 10 records per test point and 100 records per reference point will be averaged. The average of each point is based on 24 beacons. Then at each point in the radio-map data and testing data will have 24 values.

4.2 BLE Selection

The first thing to do is to find the right BLE. At this stage, the BLE selection process can be done by finding the best RSSI value on the data testing point. This BLE determination is also intended to find out how much BLE data will be processed.

4.3 Reference Point Selection

After selecting BLE. Then all data at the reference point for the selected BLE will be calculated using Euclidean Distance to find the closest RSSI value that leads to the best reference point to be used. There are several things to note. The calculation of Euclidean Distance is carried out based on the respective RSSI values at the test point and RSSI at the reference point in the selected BLE. After all, the reference point data in the selected BLE are processed by Euclidean Distance. Furthermore, sorting can be done to find the 3 smallest RSSI Euclidean Distance values at 3 reference points, then these 3 reference points will be x1y1, x2y2, and x3y3.

4.4 Distance Estimation

The estimation process will be carried out using the log distance path loss model. The Calculation of distance estimation is very important in path loss as well as in this study. Then the path loss can be used to estimate the distance from the transmitter to the receiver.

$$d = d_0 10^{\frac{RSSI_0 - RSSI + X}{10n}} \quad (5)$$

There will be 3 calculations for d ($d1$, $d2$, $d3$) from 3 different selected reference point. Here, at this stage reference point act as a BLE. Every d will have several sub calculation ($d1_1$, $d1_2$, $d1_3$,... $d3_n$) if several BLE is selected. d_0 is the selected BLE distance to the selected reference point, so d_0 must have different values.

4.5 Find Radius

Because d is the distance of selected BLE to a testing point. So, to find the radius (r), which is the distance from the selected reference point to testing point, we used the following equation:

$$r = abs(d - d_0) \quad (6)$$

Also there will be 3 r calculation ($r1$, $r2$, $r3$) from 3 selected reference point. And there will be several sub calculation for r ($r1_1$, $r1_2$, $r1_3$, ... $r3_n$) depend on how many BLE selected is used. d_0 is the same value as the previous process and has a different value of each selected reference point and BLE. The result of r is absolute so it always has a positive value. If there are several results from several BLE selection, then just get the averaged results.

4.6 Position Estimation

After getting x1y1, x2y2 and x3y3 in the previous process. There will be 3 reference points that will be used, and the 3 reference points have also been calculated to get an approximate distance/radius. So then to determine the position used the trilateration method as in the following equations. Expand out the squares in each of the equations (4):

$$X^2 - 2_{x_1 x} + x_1^2 + y^2 - 2y_1 y + y_1^2 = r_1^2$$

$$X^2 - 2_{x_2 x} + x_2^2 + y^2 - 2y_2 y + y_2^2 = r_2^2 \quad (7)$$

$$X^2 - 2_{x_3 x} + x_3^2 + y^2 - 2y_3 y + y_3^2 = r_3^2$$

Subtract the second equation from the first:

$$(-2x_1 + 2x_2)x + (-2y_1 + 2y_2)y = r\frac{2}{1} - r\frac{2}{2} - x\frac{2}{1} + x\frac{2}{2} - y\frac{2}{1} + y\frac{2}{2} \quad (8)$$

Now subtract the third equation from the second:

$$(-2x_2 + 2x_3)x + (-2y_2 + 2y_3)y = r\frac{2}{2} - r\frac{2}{3} - x\frac{2}{2} + x\frac{2}{3} - y\frac{2}{2} + y\frac{2}{3} \quad (9)$$

Rewrite these two equations using A, B, C, D, E, F values. Resulted the following system of 2 equations:

$$A_x + B_y = C \quad (10)$$

$$D_x + E_y = F$$

And the solution of this system is:

$$x = \frac{CE - FB}{EA - BD} \quad (11)$$

$$y = \frac{CD - AF}{BD - AE}$$

5. EXPERIMENTS

5.1 Dataset

There will be 24 BLE. Figure 2 shows a design for each BLE. Data collected using a smartphone. The user will input the x and y position, and then click the search to retrieve the RSS signal. There are 2 kinds of fingerprints. The first is a reference point and testing point. The reference point can act as a reference BLE position and used as a substitute BLE for the reference position. The second is the testing point act as a real point position and this point will be estimated. There are 54 reference points and 156 testing points. Each BLE will transmit an RSS signal to the smartphone. The RSSI value and the coordinate will represent every location to create a database. There are 100 data samples from each reference point and 10 data samples from each testing point.

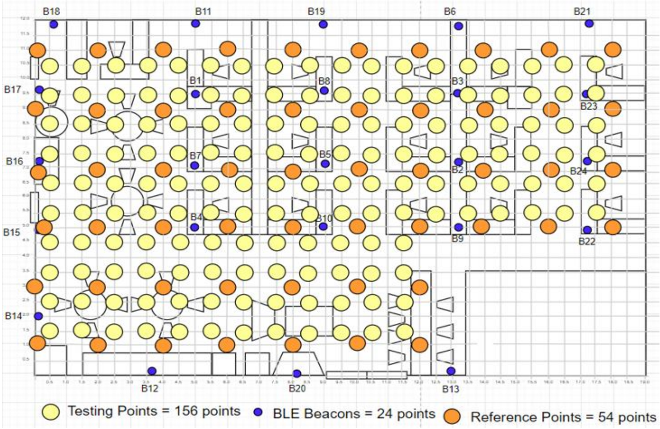

Figure 2: Mapping of BLE, Reference Point and Testing Point.

5.2 Experimental Design

Each BLE configured with 0 dBm transmit power and 200 milliseconds refresh rate. The BLE using the best settings. Placed around the walls and pillars around 1.2 meters from the ground. There will be 2 types of data: radio-map data and testing data. Radio-map data is from the reference point. Collected from the fingerprinting offline phase. And testing data from the testing point. Collected from the fingerprinting online phase to evaluate the performance.

In the proposed hybrid method. The first thing to do is to select the best BLE based on the RSSI value (testing data). And also, at the same time determine how much BLE data is selected for processing. If the best BLE has selected. On radio-map data, only selected BLE will be processed using Euclidean Distance. This calculation is to find the closest distance from the reference point to the test point. The calculation of Euclidean Distance based on RSSI of selected BLE on test point (testing data) against RSSI of selected BLE on every reference point (radio-map data). There are results for all reference points. Sorting to find the smallest Euclidean Distance and select 3 closest reference points as x1y1, x2y2, and x3y3.

Furthermore, the distance estimation is carried out using the log distance path loss model. There will be 3 calculations from the 3 selected reference points. If several BLE is selected at the beginning, then based on the reference point there will be several sub calculations. After that, for the radius or distance from each reference point to the test point. Same as before, there will be 3 calculations to get this 3 radius or distance. However, if several BLE has selected then there will be several sub calculations as well. The value calculated by the radius will always be an absolute value which is always positive. If there are multiple results from this calculation, then these values will be averaged. When x1y1, x2y2 and, x3y3 are known and the estimated distances of r1, r2 and, r3 are known. Furthermore, the final stage is the position estimation using the trilateration method.

To determine the performance of the hybrid method, experiments using the trilateration method will also be carried out. The first process is to select the best BLE through the RSSI value. After getting 3 BLE act as x1y1, x2y2, and x3y3. Then each BLE select 1 reference point with the closest distance. After that, 3 calculations using the log distance path loss model based on 3 selected BLE and 3 nearest reference points from each BLE. Result 3 in distance or radius estimation used for the trilateration method with the 3 selected BLE.

5.3 Experimental Results

Now all radio-map data and testing data have been processed with the hybrid method which is the combination of fingerprinting and trilateration. And also, the trilateration method. The results of the hybrid method shown in Table 3. The lowest average error is using the closest 1 beacon data with 244,506 cm and the highest average error is using 24 beacon data with 971,624 cm. If only 1 closest data beacon, the min error is 3,362 cm and the max error is also the lowest with 860,943 cm. Meanwhile, if more than 1 beacon data is used, the min error value will increase, and the max error will also be higher. The results experiment for the trilateration method is presented in Table 4. The average error for this method is 672.239 cm. Min error 7.777 cm for test point 1450, 950. And for max error has the highest value which is 18013.635 cm.

Table 3: Error Results of Hybrid Methods

Data Beacon	Average Error	Min Error	Max Error
1 data beacon	244.506875	3.3624112	860.94307
2 data beacon	322.945864	4.9314715	1601.55982
3 data beacon	314.747222	23.718965	2555.33486
4 data beacon	334.853155	10.115959	3317.31024
5 data beacon	300.835619	16.577254	1423.93704
6 data beacon	318.609481	12.566896	1782.6227
7 data beacon	310.554044	35.753821	1776.66847
8 data beacon	301.488297	29.625866	1894.76784
9 data beacon	308.955514	17.947205	1518.36812
10 data beacon	325.873325	38.096404	3207.7963
11 data beacon	300.644285	15.793059	1371.62934
12 data beacon	337.24121	18.616472	1771.28693
13 data beacon	333.424929	27.761744	1659.22489
14 data beacon	357.494996	36.843377	2675.30879
15 data beacon	335.859516	22.806191	1328.16089
16 data beacon	338.397637	50.879697	1862.56336
17 data beacon	338.429202	35.5035	1324.14465
18 data beacon	364.30798	29.779082	1934.69781
19 data beacon	363.761736	34.108725	1794.49652

20 data beacon	397.530072	50.261462	1819.70129
21 data beacon	438.315317	63.767828	1967.09815
22 data beacon	487.878986	25.364449	2120.31313
23 data beacon	626.17406	73.844259	5925.57087
24 data beacon	971.624312	16.865066	8395.39179

Table 4: Error Results of Trilateration Method

Data Beacon	Average Error	Min Error	Max Error
3 data beacon	672.2392597	7.7778035	18013.6352

6. CONCLUSION AND FUTURE WORKS

From the results can be concluded that the proposed hybrid method proved to have better accuracy and less error rate than using just the trilateration method. And if the distance between the testing point and the beacon is getting farther, the interference will be increasing, and the estimated error will also be higher. So, it is better to process the closest 1 beacon and 3 reference points which has the best RSSI value with the least interference.

For future work, it is preferable to place the beacon at a distance from the wall to reduce signal reflection which affects the RSSI quality. Better placement of BLE close to a reference point. It is better to add a reference point than BLE and it is better to use a reference point closest to the test point rather than a reference point closer to BLE. Try to keep in the room no signal interference with WIFI. Each BLE can use a different channel and not interfering with each other. Data for each reference point can be more than 100 samples and data for each testing point can be more than 10 samples.

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