Development of real-time monitoring BLE-LoRa positioning system based on RSSI for non-line-of-sight condition

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ABSTRACT

Indoor positioning has become popular in this decade and is used to locate users or objects in indoor environments. This is because global positioning system (GPS) is not efficient for indoor use due to the multipath fading effect. This research is about development bluetooth low energy (BLE) indoor positioning system with the aid of long range (LoRa) network and guideline on selection of the BLE beacons. Next, positioning systems are developed consisting of BLE beacons, a transceiver of hybrid BLE-LoRa module, a LoRa receiver and Raspberry Pi as real-time monitoring. The received signal strength indicator (RSSI) and BLE Mac address from BLE beacons received via LoRa network are analyzed using the positioning algorithm designed in MATLAB. The positioning algorithm incorporates distance estimation, filter implementation and trilateration technique. The estimated location is analyzed with the root mean square error (RMSE) and cumulative distribution function (CDF). According to the results, implementing the filter reduces the positioning accuracy error, achieving 90% accuracy of positioning error less than 1.20 meters for the whole testbed. Finally, the algorithm is embedded into Raspberry Pi to view the location via desktop.

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1. INTRODUCTION

Presently, positioning systems are an essential factor in everyday human life. The evolution of positioning systems is critical to advancing mankind's civilizations because it can be utilized in various areas such as security, monitoring, tracking, and health care [1]. Global positioning system (GPS) is a satellite navigation system utilized to evaluate the location of an object, particularly for outdoor areas whereas indoor positioning system (IPS) would be most common used for inside high-rise or indoor surroundings.

Indoor positioning is divided into three categories: network-based, inertial, and hybrid systems. IPS is a technology that substitutes GPS to determine a user's and a device's position in enclosed spaces [2]. Wireless communication is utilized under a network-based system; their examples are WiFi-based, long range (LoRa)-based and bluetooth-based positioning systems. An inertial-based system includes a self-contained detector or sensor system to predict the user's position [3]. The hybrid system combines multiple approaches or techniques for measuring the user's location [4]. Hybrid combines two or more different wireless technologies in one system, such as combining WiFi and bluetooth technology [5].

Bluetooth low energy technology is a wireless technology implemented primarily at wireless personal area networks (WPAN) by the bluetooth special interest group (SIG) [6]. Bluetooth low energy (BLE) beacons have been utilized for indoor localization based on their low price, low energy consumption, easy fix, and widespread availability for mobile gadgets. Because of the short transmission reaching distance, the transmission range of a BLE beacon is lower than that of a WiFi device [7]. Their tiny size, beacons may be put in a variety of locations. BLE beacons run on the same 2.4 GHz frequency as old bluetooth, and both systems use the same modulation algorithm, gaussian frequency shift keying [8].

Received signal strength indicator (RSSI) trilateration is a technique that heavily relies on RSSI and uses the path loss propagation model to determine the distance between the destination point and the transmitter, commonly referred to as the point of reference [9], [10]. The trilateration approach is used to determine the precise location by utilizing the intersection points created by three circles of BLE beacon's transmission range as well as the length [11], [12]. The distance determined by the path loss model is critical for calculating the location of a point [13], [14]. The IPS based on trilateration is a simple and low-cost system since the receiver RSSI data is easily extracted [15], [16]. If the trilateration approach is used with another method or technology, the accuracy of the IPS can be increased [17], [18].

Research regarding the trilateration approach was being used to construct a proposed portable indoor localization system utilizing Android and BLE [19]. Resetting beacons are performed to alter RSSI readings at a distance of one meter to improve the accuracy of a predicted range. That gadget would show the individual actual position and path towards the target. But using only basic trilateration will result in mitigation of signal as RSSI has heavy fluctuation because of the multipath fading effect.

The overall efficiency of the trilateration approach in indoor localization using BLE transmitters was investigated. The data are classified into three types: one, mean of five RSSI and mean of ten RSSI [20]. The Received signal data are used to calculate the distance difference. It has been discovered that when the measurement size is raised, the distance loss decreases significantly. Numerous RSSI readings can indeed be utilized to increase indoor location precision.

2. METHOD

The BLE-based indoor positioning system is designed and developed utilizing the RSSI. The first step of the system is setting up the BLE beacons at particular positions. The measurements are taken at the broadband and networking (BBNET) Lab, FKEKK, UTeM. Figure 1 depicts the BLE positioning system setup where the BLE beacons will transmit the RSSI, timestamp and the mac address of each beacon to the transceiver within the distance range of 20m. The transceiver with the BLE module on ESP32 combined with the dragino LoRa bee module (915 MHz) will receive the BLE raw data and send it to the receiver via the LoRa module, which has a range of up to 500 m. In contrast, the receiver consists of the LoRa module and Arduino UNO. All the raw data is then transmitted to the Raspberry Pi. A real-time BLE location estimation algorithm is being embedded into the Raspberry Pi, and the location estimation is displayed on the desktop.

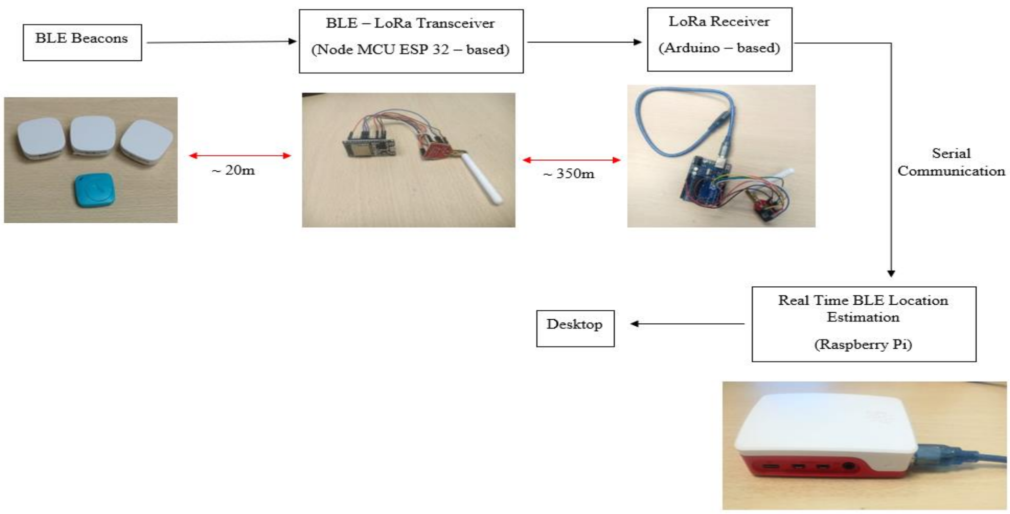


Figure 1. BLE positioning system setup

Figure 2 shows the flowchart of the overall BLE positioning system. Phase 1 is the BLE system setup, design and data collection, whereas phase 2 is designing the BLE location estimation algorithm. Meanwhile, phase 3 is embedding the algorithm in Raspberry Pi.

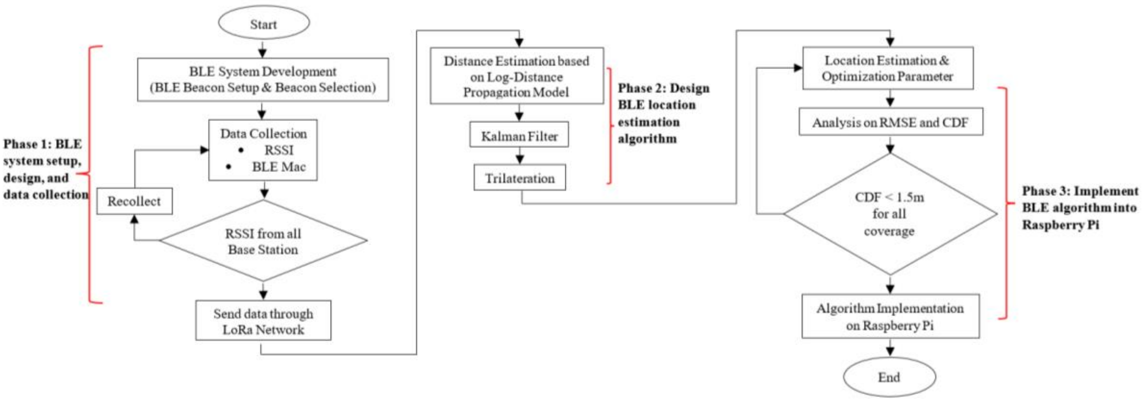


Figure 2. Flowchart of the BLE positioning system

2.1. Data collection

BLE beacons are set in broadcasting mode and attached to the walls at 1.7m height. Each BLE beacon has its own mac address, which eases the classification based on the address when the RSSI is being collected. The transmitters are placed at three different positions at the BBNET lab in non-line-of-sight (NLOS) conditions. Figure 3 shows the arrangement of the beacons at the lab within the size of 10 meters x 20 meters. The yellow triangle-shaped points represent the BLE transmitters, whereas the black dots represent the multiple reference points. 100 raw RSSI are collected using the transceiver BLE-LoRa module designed for each multiple reference point and send to the end LoRa receiver. The location and positioning algorithm is being designed and analyzed in MATLAB before being embedded into the Raspberry Pi using Python script for real-time implementation.

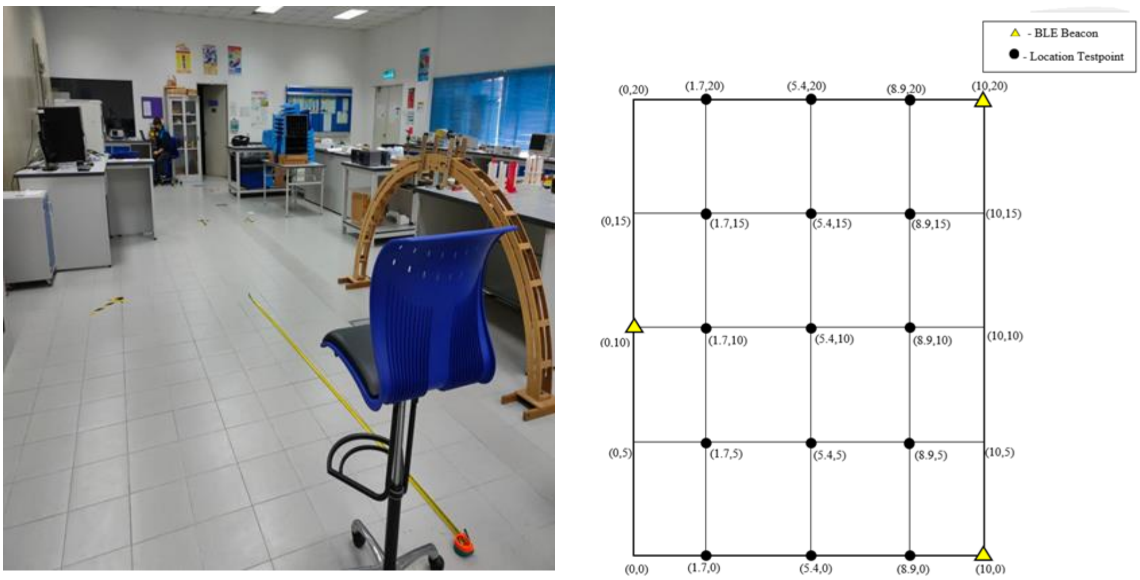


Figure 3. BLE positioning system grid set up in BBNet lab

2.2. Distance estimation

The RSSI level is analyzed using MATLAB software. Distance estimation is done by a path loss model, which uses log-distance propagation model as shown in [21],

$$RSSI = 10n \log_{10} d + A \quad (1)$$

where n = path loss exponent, d = distance from the transmitter, and A = reference value of RSSI at 1 meter away.

The equation is then arranged to make the *d* as the subject, as it is the particular parameter that should be calculated. Path loss exponent value differs according to the environment that is used in the experiment. In this experiment, for NLOS condition *n* = 4.0 as it is the environment obstructed in buildings.

$$d = 10^{\left(\frac{RSSI-A}{10n}\right)} \quad (2)$$

2.3. Kalman filter

Kalman filter is implemented as part of the location estimation algorithm. This filter has a few iteration procedures that incorporate the error covariance and the prediction state, the estimation update with Kalman Gain and the output that has been calculated. Eventually, error covariance calculations demonstrate how to approximate estimations are updated as fresh input towards the loop. Figure 4 depicts the Kalman filter construction, which has a measurement input and one estimation result. In the state transition matrix, there are four system models, A which is the state transition matrix, H the state of measurement matrix, Q is the covariance matrix of transition noise whereas R the covariance matrix of measurement noise. This filter is implemented after distance estimation to counteract and correct for data volatility caused by reflection, refraction transmission to the receiver [22].

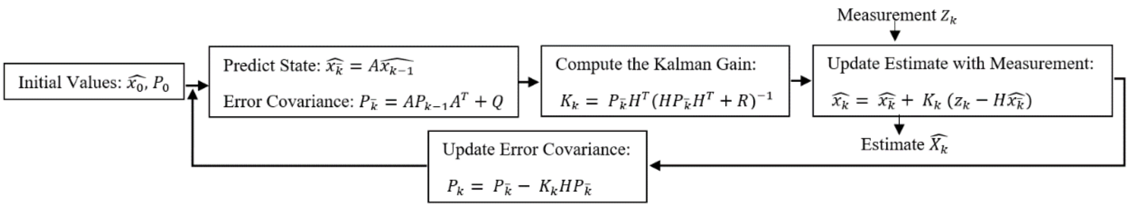


Figure 4. Kalman filter algorithm

2.4. Trilateration

After obtaining the new estimated distance, trilateration is used to estimate the location in 2D (x,y), where the position of the base station must be known. All the nodes are span out on the same plane which considers the three beacons to be B1, B2 and B3, which has the distance of d1, d2, and d3 to the target node as shown in Figure 5 [23]-[25]. The new estimated distance from Kalman filter as d1, d2, and d3 are used to calculate the final position estimation *(x,y).*

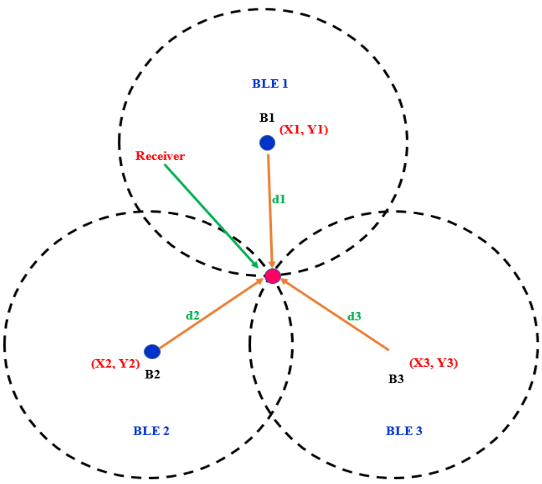


Figure 5. Trilateration technique

The formula for all the circles in one plane as shown in [26]:

$$Circle\ B1: {d_1}^2 = (x - x_1)^2 + (y - y_1)^2$$
$$Circle\ B2: {d_2}^2 = (x - x_2)^2 + (y - y_2)^2$$
$$Circle\ B3: {d_3}^2 = (x - x_3)^2 + (y - y_3)^2 \quad (6)$$

in (6) is being solved using the simultaneous equation to form the (7).

$$x(x_3 - x_2) + y(y_3 - y_2) = \frac{({d_2}^2 - {d_3}^2) - ({x_2}^2 - {x_3}^2) - ({y_2}^2 - {y_3}^2)}{2} = v_a$$
$$x(x_1 - x_2) + y(y_1 - y_2) = \frac{({d_2}^2 - {d_1}^2) - ({x_2}^2 - {x_1}^2) - ({y_2}^2 - {y_1}^2)}{2} = v_b \quad (7)$$

By solving both in (7), the intersection points 'x' and 'y' can be obtained by both as shown in the (8):

$$y = \frac{v_b(x_3 - x_2) - v_a(x_1 - x_2)}{(y_1 - y_2)(x_3 - x_2) - (y_3 - y_2)(x_1 - x_2)}$$
$$x = \frac{v_a - y(y_3 - y_2)}{(x_3 - x_2)} \quad (8)$$

values of X and Y gives the estimated location for the receiver node. As there are 100 RSSI collected data for each multiple reference points will return each reference point's 100X's and 100Y's. All the location's estimation points are being analyzed by the location error using the root mean square error (RMSE) and the cumulative density function (CDF).

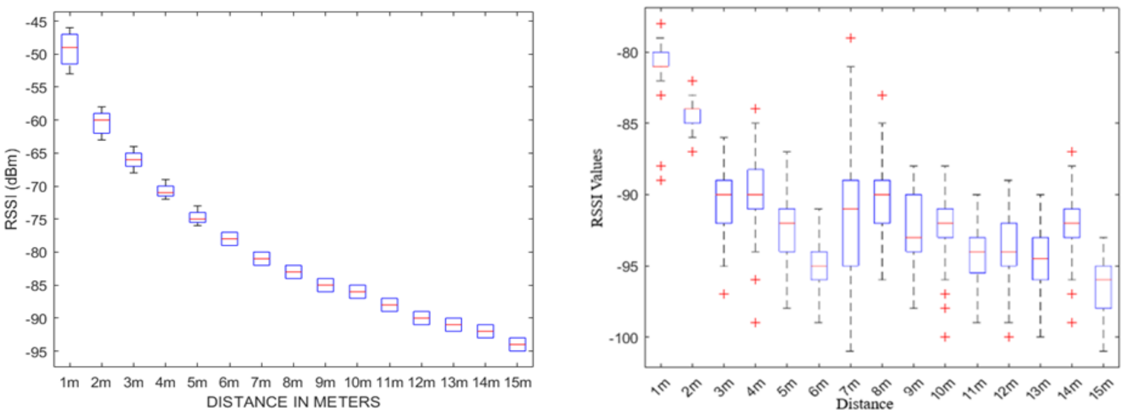
$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(x_{actual} - x_{estimated(i)})^2 + (y_{actual} - y_{estimated(i)})^2}{N}} \quad (9)$$

3. RESULTS AND DISCUSSION

3.1. BLE beacons selection

There are 2 types of beacons that are initially tested for the BLE positioning system. One is April Beacon (EEK-N) nRF 52810, and the other is NRF 52810 ABSensor N01. The sensitivity of BLE beacons has a significant effect on positioning accuracy. Hence, an analysis of beacon selection is needed to decide which of the BLE beacon is suitable for this NLOS indoor positioning. In this case, the RSSI is being analyzed to choose the best beacon by collecting the RSSI starting from 1 meter up to 15 meters in range.

Figure 6 show the RSSI boxplot for each distance of two different beacons. Boxplot is chosen to give the whole idea of RSSI distribution across the testbed in the lab. Based on RSSI distribution in Figure 6(a) and (b), April Beacon (EEK-N) nRF 52810 performs better than NRF 52810 ABSensor N01 beacon. The EEK-N has a consistent RSSI distribution pattern toward all distances, while the N01 beacon shows wider distribution especially at distance from 7m-9m; thus, the positioning accuracy is low. Therefore, April Beacon (EEK-N) NRF 52810 has been selected for positioning in this experiment.



(a) (b)

Figure 6. These figures are; (a) RSSI versus distance for April Beacon (EEK-N) nRF 52810 and (b) RSSI versus distance for NRF 52810 ABSensor N01 beacon

3.2. RSSI and distance estimation

There is a fluctuation of RSSI level when the RSSI is being measured due to indoor multipath fading effect as shown in Figure 7. Each BLE beacon has its own fluctuation difference as each is placed at different positions. The log-distance propagation model is used to estimate the distance from the transmitter to the receiver. Subsequently, Kalman filter is implemented to mitigate the multipath fading effect, and the new distance is estimated again. Both distance estimation with and without the Kalman filter has been analyzed. Figure 8 shows the difference between the distance estimation plotting with and without the Kalman filter at a static position. The blue line represents the distance estimation without the Kalman filter, while the red line represents the distance estimation with Kalman filter.

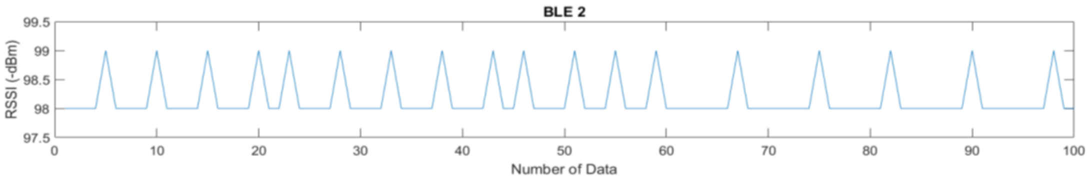


Figure 7. RSSI fluctuation

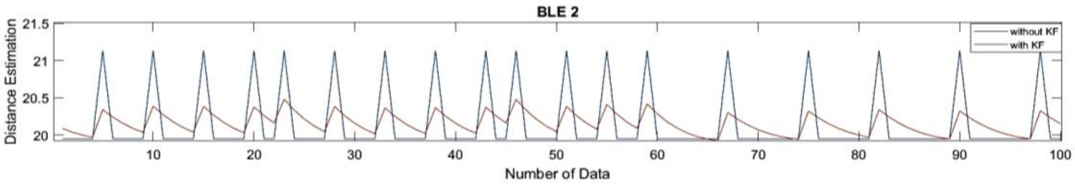


Figure 8. Distance estimation with and without Kalman filter for one BLE beacon

3.3. Trilateration for NLOS scenario with and without Kalman filter

Figure 9 shows the trilateration for the NLOS condition at the center coordinate (5.4,10). The green circle point represents the actual point of the receiver location, the blue cross point represents the estimated location of the receiver without the Kalman filter, and the red dots represent the estimated location with the Kalman filter. The measurement and analysis for the location estimation are done with 100 data samples. Implementation of the Kalman filter shows that in overall it is less error the than the estimated position without the filter. In this coordinate, the error for positioning has been the least compared to the other reference point, which is 0.280710 m.

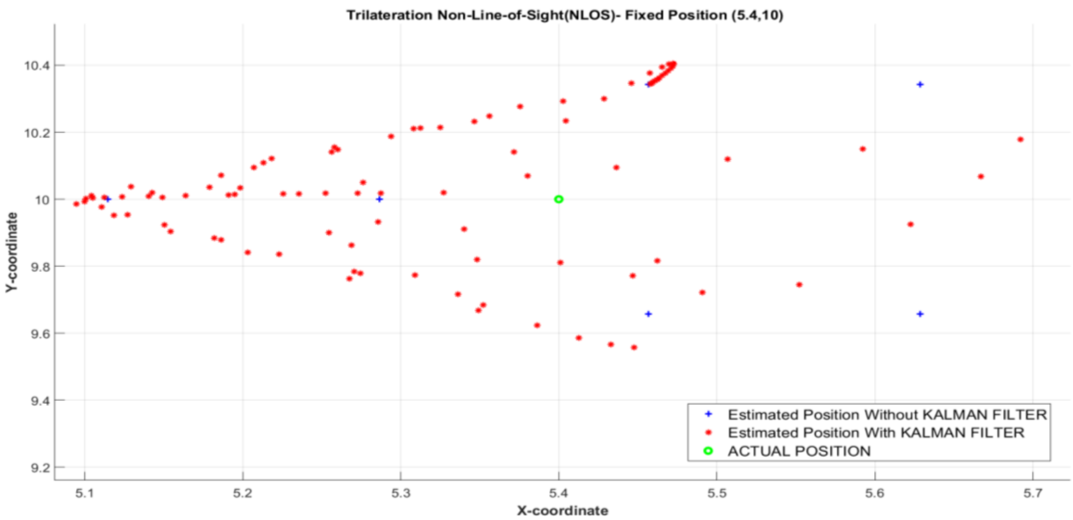


Figure 9. Trilateration for the coordinate (5.4,10)

3.4. Analysis of positioning error

Figure 10 shows the location error distribution in boxplot form for all the reference points (please refer Figure 3) with the implementation of the Kalman filter. Among the 13 points, the centre coordinate (5.4,10) shows the least error in location with a median of ~0.2605 meters. In contrast, the coordinate ath the edge (8.9,20) has the most prominent error distribution and median of ~1.8418 meters. There are also outliers in error distribution at this particular point. These indicate that the location error at the edge of the lab is dispersed and scattered more widely than at the other part position. It can be seen that the centre position has lower distribution compared to the position at the edge.

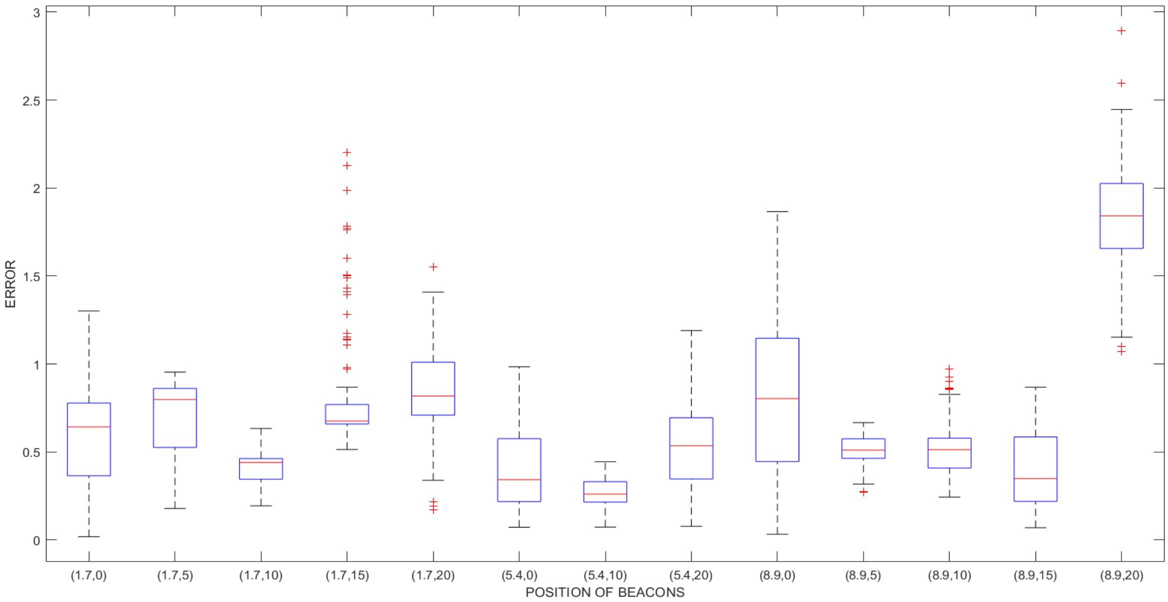


Figure 10. Boxplot distribution of all reference points in NLOS condition

Table 1 shows the positioning error using the Kalman filter for BLE Positioning in NLOS condition. It can be concluded that for all the reference points, using the Kalman filter. Improves the accuracy of the estimated position near the actual position compared to the estimated positions that are being retrieved without the filter.

Table 1. RMSE of positioning

Actual Position of user	Without Kalman filter	With Kalman filter
(1.7,0)	0.88966209	0.65199594
(5.4, 0)	0.83371475	0.462067625
(8.9, 0)	1.24778239	0.934622423
(1.7, 5)	0.7764251	0.731208532
(8.9,5)	0.43815096	0.320817049
(1.7,10)	0.46189283	0.420824762
(5.4,10)	0.30721428	0.280710886
(8.9,10)	0.56998158	0.546382969
(1.7,15)	0.96120941	0.927724978
(8.9,15)	0.605468	0.438303492
(1.7,20)	0.92742464	0.873136535
(5.4,20)	0.86162955	0.582461266
(8.9,20)	2.04527125	1.874055269

3.5. CDF

Figure 11 depicts the CDF of BLE positioning system for NLOS condition in BBNet lab. From the experiment the proposed algorithm incorporated with Kalman filter accurately estimates 90% of the position has positioning error less than 1.20 meters. Whereas without the implementation of the Kalman filter the error is 1.38 meters for the whole area of the testbed.

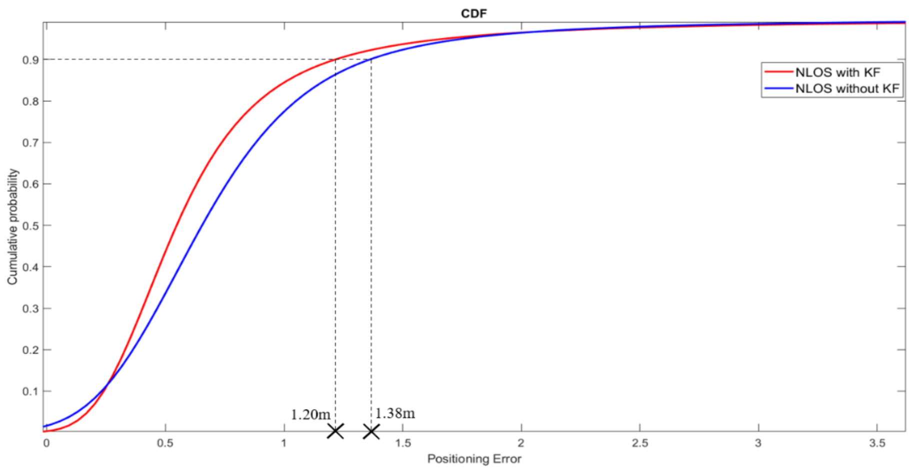


Figure 11. CDF error position for total reference points

After the BLE positioning algorithm has been designed and analyzed in MATLAB. The algorithm is then written in Python script and implemented into Raspberry Pi. The display of BLE location estimation can be viewed when executing the script in real-time.

4. CONCLUSION

Summing up, BLE positioning system is being developed successfully by implementing the technique of BLE beacon selection to choose the best beacon. Next, the positioning algorithm which consists of log-distance propagation model, filtering and trilateration technique, is being designed and implemented on the Raspberry Pi. The Kalman filter are used to reduce the fluctuation effect in distance estimation before applied in the trilateration algorithm. From the results that are being analyzed, the coordinate at the centre has the least error compared to the edge reference points. At the center point, all three BLE beacons transmits signals with strong RSSI. When compared to the edge coordinate of the testbed has the largest error as the reference point is far from two of the BLE transmitters, which have weaker signal strength. Besides, the CDF of positioning error for the whole testbed is less than 1.20 meters with the Kalman filter, whereas the error is 1.38 meters without the filter. Lastly, the algorithm is embedded into the Raspberry Pi to view the real-time location on the desktop.

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