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OPTIMAL SCHEME FINGERPRINTING LOCALIZATION FOR INDOOR POSITIONING SYSTEM USING BLUETOOTH LOW ENERGY (BLE)

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Abstract. *Recent developments in the field of wireless communication technology have made it possible to realize the concept of indoor positioning system (IPS). This condition was supported by increasing use of smartphones which have been embedded a wireless technology such as Wi-Fi, Bluetooth and other latest technologies in its development. Bluetooth low energy (BLE) has become one of candidate wireless technologies for IPS implementation. Many researchers have carried out various studies on indoor positioning and localization using BLE technologies. However, most of studies still focus on how to find the methods and algorithms that can be used to obtain distance and accuracy, few specifically focus on the scheme and placement of BLE. Therefore, this research was conducted to find the most optimal scheme and placement of BLE. In this paper is proposed a scheme by combining placement of BLE using the fingerprinting and weighted sum method. The proposed scheme reduces the number of mean of error by 3.0 m compared to normal localization scheme.*
Keywords: Indoor positioning, Bluetooth low energy (BLE), Fingerprinting localization, Weighted sum

1. **Introduction.** Global positioning system (GPS) is now widely applied in various fields, for navigation purposes, determining the coordinates of a location, distance, position tracking and others. GPS technology is embedded in mobile devices such as smartphones, almost all smartphone devices are equipped with GPS technology, so GPS is one of the most popular technologies used by the wider community to aid in determining the location, distance, positioning, navigation and tracking that is quite accurate and reliable. However, GPS has shortcomings to determine the distance and position of objects in the indoors location [1]. Consequently, attention to find an alternative for indoor positioning system (IPS) has been increasing rapidly. Researchers have carried out various studies on indoor positioning technologies such as the Bluetooth [2], ultra-wideband (UWB) [3], radio frequency identification (RFID) [4], micro-electro-mechanical system (MEMS) [5], wireless local area networks (WLAN) [6], computer vision [7], magnetic fields [8], ultrasonic [9], and infrared signal [10].

Since Bluetooth version 4.0 released in 2010, also known as Bluetooth low energy (BLE) or smart Bluetooth, BLE has become one of the wireless technologies many researchers claim that. BLE works with ultra-low power consumption [11] and has a smaller data exchange latency than the previous version [12]. Many researches claim that BLE technology can be used in IPS and that the experiments performed showed results of high accuracy [13].

However, most of studies still focus on how to find the types of technology and algorithms that can be used to obtain distance and accuracy, few specifically focus on the

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scheme and placement of BLE. Therefore, this research was conducted to find the most optimal scheme and placement of BLE to get high accuracy using fingerprinting technique. The objective of this study is to provide an optimal scheme and placement of BLE to get high accuracy as a reference for the IPS implementation.

2. Related Works.

Research in indoor positioning and indoor localization is now quite advanced. Various technologies and techniques in IPS have been proposed. Technologies and techniques for implementing IPS are briefly summarized in this section.

2.1. Indoor positioning technologies.

The technology of indoor positioning mostly uses radio frequency-based (RF-based). RF-based in the localization system generally consists of two main components, transmitter and receiver, which are both connected through radio signals [14]. The first indoor localization that uses radio frequency is known as RADAR [15]. RADAR is designed to find and track users in the building by gathering signal strength information in several locations of receiver and using that information to estimate positions.

RFID has the main components namely RFID reader and RFID tags and uses radio waves to store and retrieve data between RFID readers and RFID tags [16]. LANDMARC: Indoor Location Sensing Using RFID [17] is the first indoor localization using RFID to determine the location in the building. This system uses active RFID tags pinned to objects to be tracked and places multiple RFID readers in certain locations. Signal strength of each RFID tag is captured and measured through an RFID reader and calculated using the k-nearest neighbors (k-NN) method to determine the location of the RFID target.

Another RF-based technology in IPS is wireless local area network (WLAN). WLAN as an infrastructure has been widely used in any areas. Almost every building is now available wireless fidelit (Wi-Fi), including in office buildings, restaurants, educational facilities, public areas and even at home. WLAN is a technology used for communication and exchange of wireless data on a computer network within a range of distances between 10-20 m from an access point [16]. Indoor positioning system based on WLAN works by utilizing several access points (AP) to determine the target position in a particular area. And the coverage area can be expanded by installing additional access points, so that targets can still be tracked as long as they are within reach and not out of reach [18]. Ekahua positioning system [19] is a popular one that uses WLAN infrastructure.

Bluetooth low energy (BLE) is great chance of becoming a candidate in IPS technology. BLE is used for wireless data exchange with a short distance between 10-100 m with Bluetooth 2.0, and in IEEE 802.15.1 Bluetooth is defined as a standard wireless personal area network (WPAN) that runs on a 2.4 GHz frequency and has the ability to transfer data it is 1-3 Mbit/s [19]. In June 2010, the Bluetooth version 4.0 released and introduced a new technology called Bluetooth low energy (BLE) or "Bluetooth Smart". In this version, among the two lowest layers of the BLE stack, the physical (PHY) layer takes care of transmitting and receiving bits, whereas the link layer (LL) provides medium access, connection establishment, error control, and flow control. As with the other protocols defined in BLEs, logical link control and adaptation protocol (L2CAP), generic attribute protocol (GATT), and generic access profile (GAP) operate on the upper layers [20]. A BLE device deployed in localization and IPS is called a "beacon". Recently, BLE is popular in the industry and today almost all mobile devices such as smartphones are equipped with BLE that have the ability to communicate with Bluetooth tags and can be used as readers [14]. Practical fingerprinting localization for indoor positioning using BLE was conducted by [21], they are combining traditional fingerprinting localization with weighted centroid localization (WCL). It reduces the total number of reference points over the localization area, thus minimizing both the time required for reading received signal strength indication (RSSI) and reduces the number of reference points needed during the fingerprinting learning process and makes the process less time-consuming. The RSSI measurements are affected by path loss exponent (PLE) and environment factors. Which are related to increasing of propagation distance between the transmitter and the receiver, in [22] was proposed a linear estimator for RSS-based source localization by analysing the impacts of PLE on the positioning, the estimation approach for coarse source position is put forward and then the estimated position is refined iteratively by availing the reciprocal constraint relation.

2.2. **Fingerprinting.** This method is most popular for indoor positioning and object tracking [23]. [24] also states that the fingerprinting method is the most accurate method in indoor positioning because conditions in the room are usually many barriers that affect the line of sight of the receiver and interfere with signal propagation. Scene matching technique consists of two phases, offline phase and online phase. In the offline phase, the reference node beacons are placed in a certain area, providing signal coverage from the intended area. Then the area is divided into grids, and in each grid cell, fingerprint RSSI is collected and labeled at coordinates (x, y) to make a radio map from that area. In the online phase, the position of a moving object will be detected and its x and y position will be estimated. Estimation of this position can be done by comparing the measurement of RSSI from the object with RSSI from the predetermined offline phase (fingerprinting).

3. **Proposed Method.** IPS fingerprinting using weighted sum is proposed in this study. Radio map is collected from different schemes in order to get the most optimal scheme and produce high accuracy.

3.1. **Weighted sum.** In the weighted sum method for location estimation, weight w_i is assigned to beacons when measuring the distance from a tag device. For m beacons, weighted sum is defined by the following set of equations:

$$x_w = \sum_{i=1}^{m} x_i \times \frac{w_i}{\sum_{i=1}^{m} w_i}, \tag{1}$$

$$y_w = \sum_{i=1}^{m} y_i \times \frac{w_i}{\sum_{i=1}^{m} w_i}, \tag{2}$$

where (x_w, y_w) is the estimated coordinate of the weighted sum method, m is the total number of beacons i and w_i is weight of RSSI.

The process flow fingerprinting localization process is shown in Figure 1. The next step is to calculate reference point coordinate (x, y), then collect RSSI data and store average RSSI's in database. The next step is to calculate using weighted sum method to get output coordinate. The positioning distance (D_j) between the stored RSSI value

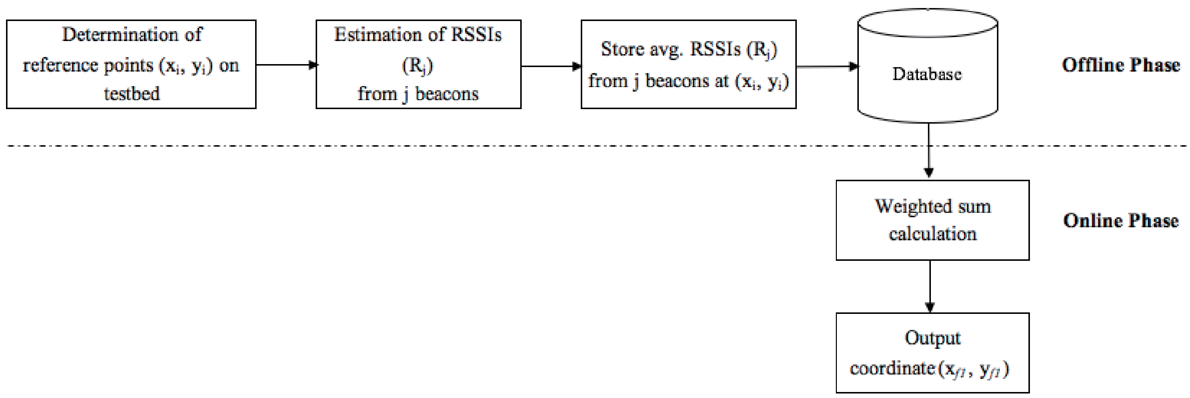

FIGURE 1. The process flow fingerprinting localization method

of ($RSSI_{offline}$) and the online collected RSSI value ($RSSI_{online}$) at jth reference point is given by

$$D_j = \sum_{i=1}^{m} \sqrt{\left(RSSI_{i_{online}} - RSSI_{i_{offline}}\right)^2}, \tag{3}$$

where i is the number of beacons from 1 to m, the total number of beacons deployment.

3.2. **Experiment setup.** There are five schematics (SCM), SCM 1 – SCM 5 shown in Figures 2-6. The schemes have different configurations and amount of BLE, detail configuration and parameter shown in Table 1. The testbed used to experiment for all schemes has length 8.2 m × 6.8 m. In all of schemes using 20 reference points and 56 testing points with amount of BLE deployment is 4 or 8, depending on schematic.

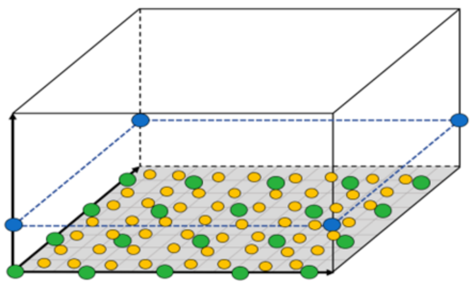

FIGURE 2. SCM 1

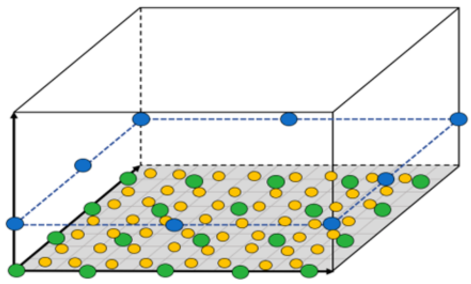

FIGURE 3. SCM 2

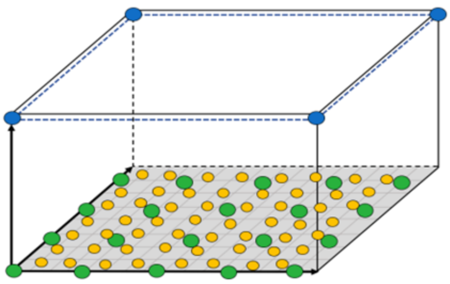

FIGURE 4. SCM 3

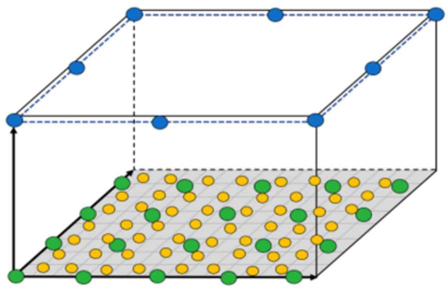

FIGURE 5. SCM 4

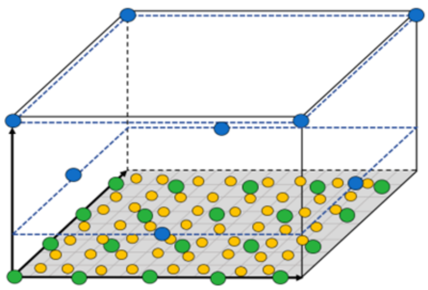

FIGURE 6. SCM 5

● BLE/beacon ● Reference point ● Testing point

The blue dot (●) is BLE deployment, the green dot (●) is reference point and the yellow dot (●) is testing point. The amount and high deployment of BLE varies depending on the scheme. SCM 1 and SCM 2 using four and eight BLE is with high beacon deployment of 1.2 m, SCM 3 and SCM 4 using four and eight BLE is with high beacon deployment of 3 m while SCM 5 using eight BLE is with combination of height beacon deployment that is 1.2 m and 3 m.

TABLE 1. Experimental condition and parameters setup for evaluation of the proposed scheme

Parameters	SCM 1	SCM 2	SCM 3	SCM 4	SCM 5
Total amount of beacons	4	8	4	8	8
Length/breadth of the room	8.2 m × 6.8 m	8.2 m × 6.8 m	8.2 m × 6.8 m	8.2 m × 6.8 m	8.2 m × 6.8 m
Height of beacon deployment	1.2 m	1.2 m	3 m	3 m	1.2 m, 3 m
Beacon transmission power	0 dBm	0 dBm	0 dBm	0 dBm	0 dBm
Beacon advertisement interval	200 milliseconds	200 milliseconds	200 milliseconds	200 milliseconds	200 milliseconds
Tx-Rx devices	Radioland NRF51822 (Beacon), Samsung Note 5	Radioland NRF51822 (Beacon), Samsung Note 5	Radioland NRF51822 (Beacon), Samsung Note 5	Radioland NRF51822 (Beacon), Samsung Note 5	Radioland NRF51822 (Beacon), Samsung Note 5
Number of reference points (N)	20	20	20	20	20

4. **Experimental Results and Discussion.** The results of experiments show that BLE placement and amount of BLE affect accuracy and error. SCM 1 and SCM 2 in Figure 7 and Figure 8 from the experimental results show the highest mean of error. These schemes use four BLE with height of beacon deployment 1.2 m.

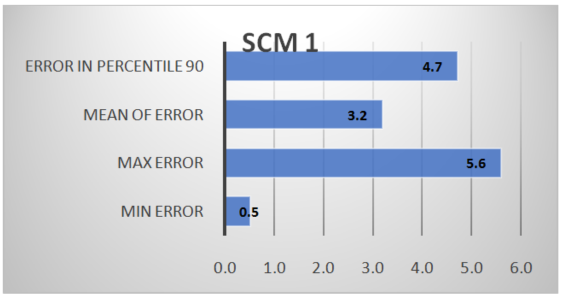

FIGURE 7. SCM 1 results

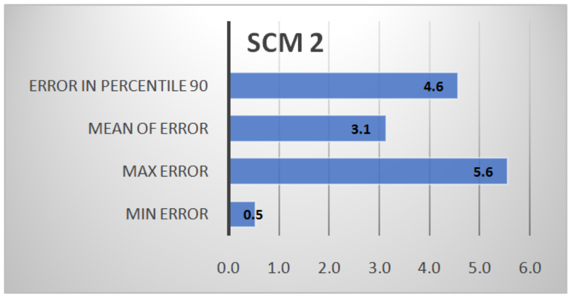

FIGURE 8. SCM 2 results

SCM 3 and SCM 4 that use eight BLE with height of beacon deployment 3 m shows better accuracy results than SCM 1 and SCM 2. Placement and amount of BLE affect the accuracies shown in Figure 9 and Figure 10.

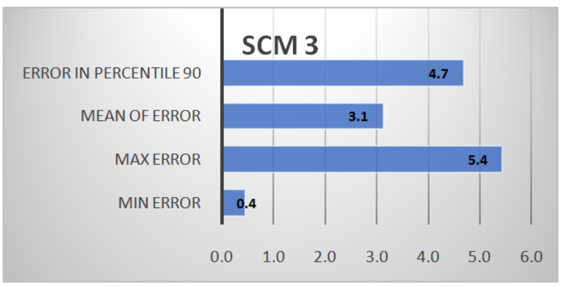

FIGURE 9. SCM 3 results

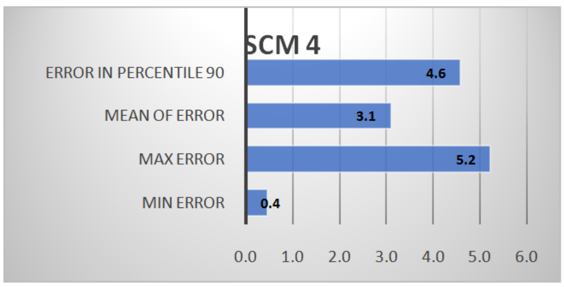

FIGURE 10. SCM 4 results

SCM 5 is the last scheme observed. SCM 5 has the highest accuracy when compared to the schemes tested. Figure 11 shows that SCM 5 yields mean of error 3.0 m.

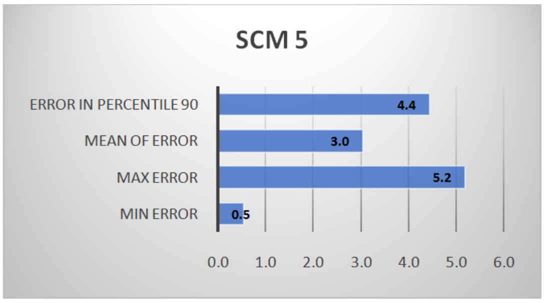

FIGURE 11. SCM 5 results

The error distribution of each testing point is shown in Figure 12. In general, the error value of each point has not a significant difference between one scheme and another.

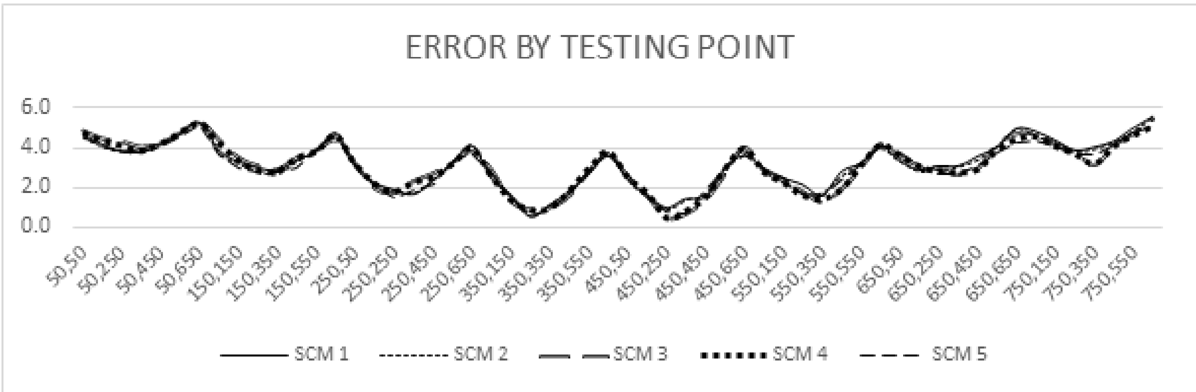

FIGURE 12. Error by testing point

The final results of the experiment are shown in Figure 13 and Table 2. This figure shows that SCM 5 has the lowest mean of error value compared with another.

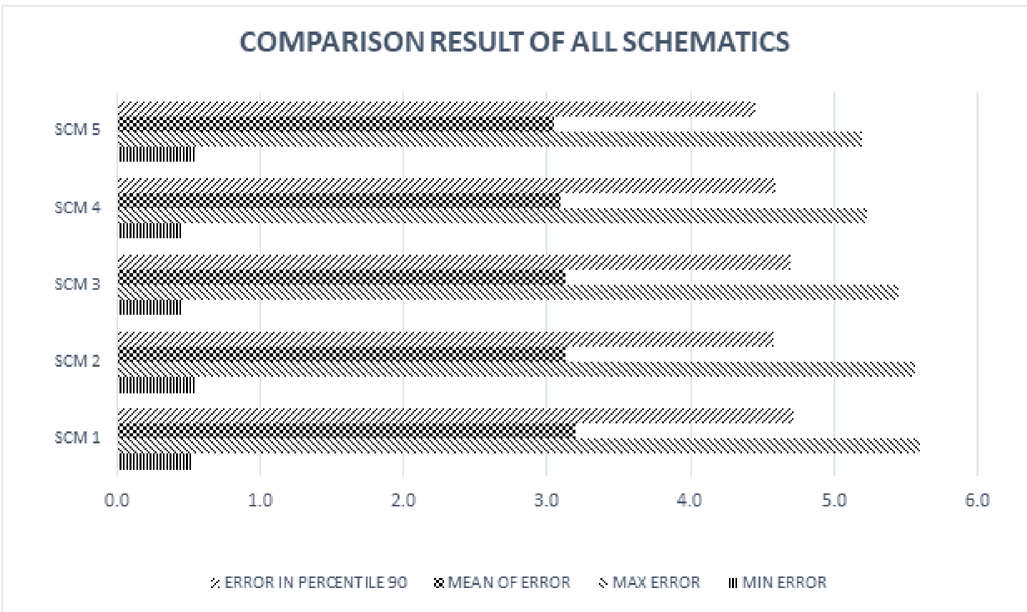

FIGURE 13. Comparison result of all schematics

Table 2. Experimental results

Schematics	Min of Error (m)	Max of Error (m)	Mean of Error (m)	Error in Percentile 90% (m)
SCM 1	0.5	5.6	3.2	4.7
SCM 2	0.5	5.6	3.1	4.6
SCM 3	0.4	5.4	3.1	4.7
SCM 4	0.4	5.2	3.1	4.6
SCM 5	0.5	5.2	3.0	4.4

5. **Conclusions.** The proposed scheme by combining of height of BLE deployment shows the acceptable accuracy value. By combining of height of BLE deployment can also increase the average of RSSI value. The proposed scheme reduces the number of mean of error by 3.0 m compared to normal localization scheme. There are five schematics that have been observed in this study; for future work, increasing the number of schemes, more different types of testbed and more combining of height of BLE deployment might will increase the number of the best reference schemes for IPS implementation.

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