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BLE Beacons Positioning Algorithm using Particle Swarm Optimization for Indoor Navigation System

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Abstract. This paper proposed a BLE beacon positioning algorithm for an accurate indoor navigation system. In this work, an indoor positioning method is proposed by joining Particle Swarm Optimization (PSO) and trilateration method to determine the optimal number and position of the BLE beacons. The impacts of BLE beacon placement were systematically assessed based on Received Signal Strength Indicator (RSSI) obtained from direct measurement. The position of BLE then, can be estimated by trilateration technique which considers the intersection of at least three BLE signals. The RSSI is analyzed and the path loss model is obtained by processing the experiment data. The results show that the proposed algorithm is relevant to be implemented in non-line-of-sight (NLOS) condition.

Keywords: indoor positioning system (IPS), particle swarm optimization (PSO), trilateration, received signal strength indication (RSSI)

1. Introduction

The demand for Indoor Positioning System (IPS) is becoming more important. Global Navigation Satellite System (GNSS) is widely used to provide navigation, location and timing information based on signal retrieved from satellite. For most of indoor applications, however, the signal experiences great attenuation due to wall and signal obstruction, which results in limited positioning accuracy. In such circumstances, when a user is indoors and obviously has no line of sight with a satellite, indoor positioning system (IPS) has gained more importance in providing directions or coordinate based on user or object location. These pervasive applications can be seen in shopping complexes, museums, hospitals and production lines.

IPS depends greatly on the availability of precise location. Position estimation can be handled by means of technologies such as wireless local area networks (WLANs) (Bruno et al., 2014; Jun and Gou-Ping 2017; Yu et al., 2020), Radio Frequency Identification (RFID) (Xu et al., 2017; Xu et al., 2018; Rose et al., 2020), magnetic-based navigation (Shu et al., 2015; Lee et al., 2018), Bluetooth (Qureshi et al., 2019; Natarajan et al., 2016), Zigbee (Guo et al., 2019), and hybrid approaches (Grottke and Blankenbach 2021). Different strengths and weaknesses offered by each of the technologies, lead to different challenges of the implementation. It can be found that a number of empirical works have been accomplished to prove that high positioning accuracy can be achieved by deploying BLE.

BLE is one of Bluetooth 4.0 protocols (IEEE 802.15.1), which operates at the 2.4GHz ISM band. A typical IPS requires BLE beacons, which periodically emit signals to be received by BLE-enabled device or mobile phone. BLE offers excellent robustness, with relatively small size, high security and low footprint on the smartphone's battery and network traffic (Davidson and Piche 2017). BLE is also economically attractive due the ability to provide 24Mbps transmission speed with higher efficiency (Zafari et al., 2019) and with good accuracy within 700m – 900m (Qureshi et al., 2019). The users can easily use their own mobile devices, whereby Wi-Fi, Bluetooth and 3G/4G signal are readily integrated and compatible with BLE's positioning functionality.

Realizing IPS leads to some challenges. The greatest challenge is to obtain an accurate localization in an indoor environment, which mostly are complicated and diverse in terms of spatial and topology layout; the existence of various blockage in different size and material, result in severe attenuation in comparison to the outdoor environment. The fluctuation is worsen (Ullah et al., 2013; Firdaus et al., 2019), as the movement of people is noticeable. In fact, in an IoT environment, communication between wireless networks and devices produces large amount of data, thereby, resulting in packet drops, retransmission, link instability and inconsistent protocol behavior (Chang 2015). Thus, consideration of environmental factors whose effects might compromise the accuracy of prediction is essential during the planning stage of BLE deployment.

As it is clear that the placement of BLE has a profound impact on the overall deployment cost, placement via trial-and-error method should be avoided. Most of the empirical works (Pinto et al., 2021; Mendoza-Silva et al., 2019; Domingo-Perez et al., 2016; Zhu and Alsharari 2015) highlighted the importance of the right placement and the exact number of BLEs. It is worth noting to consider the beacon range and positioning method too. The guidelines can be found in (Vy and Shin 2019; Kriz et al., 2016), which specified the complexity and available deployment options.

In the context of IPS deployment, most of the optimization efforts aimed to find an optimal beacon placement, making the distinction between different optimization approaches by using a classification scheme. In view of this research work, Particle Swarm Optimization (PSO) and Received Signal Strength Indication (RSSI) measurement using trilateration is applied. PSO refers to an optimization approach to determine a suitable fitness function of beacon placement. In the case of detecting method, measurement of RSSI is attractive to many, as the approach is straightforward and practical (Rose et al., 2020; Guo et al., 2019) allowing the establishment of one-to-one relationships to ensure the area of interest can be served at acceptable signal levels. It does not require sophisticated localization hardware, time synchronization and angle measurement (Jun and Gou-Ping 2017). Nevertheless, RSSI measurement is susceptible to environmental factors, which is likely to produce more error as compared to other ranging techniques. This signifies, thorough understanding of the environment, allowing us to control the system design in making sure both coverage and capacity objectives are met (Khaled and Talbi 2019). Moreover, it is found that limited accurate radio propagation particularly for WSN (El-Mouaffak and El Alaoui 2020) and some of the works are outdated due to the rapid evolution of sensors (Brena et al., 2017). As such, work to re-affirm and reassess the radio propagation model for BLE deployment is essential.

The contribution of this paper is twofold. The primary focus is to determine the optimized number and location of BLEs to be deployed in indoor environment based on PSO and trilateration techniques. As such, mobile application framework for 2D smart campus navigation map was developed from CAD floor plan. The accuracy of the proposed model is validated by conducting measurements in Faculty of Engineering and Technology, Multimedia University, Melaka. Secondly, the characteristics of prevailing propagation mechanism in indoor environment are investigated too. The paper is organized as follows. The propagation model is described in Section II. Second, the proposed PSO algorithm is outlined and elaborated in Section 3. Evaluation and result discussion of the proposed technique is summarized in Section 4.

2. Related works

Localization accuracy is regarded by many as the most important criteria of IPS implementation. Typically, IPS have been employed for various applications to meet specific goals, including tracking of objects, providing specific location information and monitoring purposes (Grottke and Blankenbach 2021). In fact, the maturity of indoor positioning technologies has gradually been put forward to obtain positioning accuracy in the range of ten of centimeters to several meters. The systematic reviews on technology adoption, localization techniques and concept, as well as fundamental limits and challenges can be found in detail in (Zafari et al., 2019; Brena et al., 2017; Obeidat et al., 2021; Geok 2021; Hassan et al., 2020).

For brevity, this section only describes the optimization technique that have been used to trade-off between improving the IPS localization accuracy and computational effort. Accordingly, there are two mainstream positioning algorithms, namely deterministic and probabilistic methods (Pinto et al., 2021). The deterministic method consists of two coarse steps. The first step is an offline phase, in which RSS are collected from a pre-built fingerprint dataset; the latter step is an online phase, whereby machine learning and algorithms data are fed into localizer for position estimation by comparing preprocessed RSSI readings and measured RSSI in real time. Fingerprinting, as pointed out by Mendoza-Silva et al. (2019) performed better in small area as compared to proximity or lateration. However, applying this approach to practice is difficult due to smartphones are moving objects (Grottke and Blankenbach 2021). For multi-fingerprinting information, usage of random forest and particle filter algorithm achieves higher precision (Jiang 2020).

The probabilistic method, on the other hand, is in form of a propagation model-based system to describe the environment by considering random component that causes change of RSS over a specific environment. In (Domingo-Perez 2016), the work starts up by considering the presence of the obstacle that possibly cause blockage between the target and sensors. Speciation and structural mutations were added to non-dominated sorting genetic algorithm (NSGA-II) based on Pareto optimal solutions obtained. The computation using an evolutionary algorithm omits the hassle in dealing with complicated algebraic derivatives; in this case, is relevant to improve the prediction, especially in NLOS condition. Similar goal was achieved in (Pinto et al., 2021) using an enhanced probability method. Other proven methods include optimization of calculated distance (Zhu and Alsharari 2015), filtering and calibration of measured RSSI (Nguyen et al., 2017) to eliminate the abnormal data. Trusted-range model (Vy and Shin 2019) makes use of reliable of RSS range from nearest neighbor nodes by classifying RSS obtained into a certain level of range. Finding shows the model performed better as compared to conventional triangulation, especially in a short-range communication. Higher accuracy can be achieved by deploying a higher density of beacon nodes (Kriz et al., 2016).

In summary, various research findings related to optimization approach to represent the ways the positioning technology is applied. Table 1 summarizes a number of relevant research works that focus on the optimization and detection method.

Table 1: Review of existing BLE IPS optimization algorithm and detection method

Ref	Optimization method	Detection method	Environment	Accuracy	Beacons	Remarks/ Limitation
[12]	Grid particle filter and Bayesian filter	Fingerprinting/ lateration	-	Accuracy increases up to 67%	-	Fingerprinting requires pre-measurement signal map data.
[19]	BLE RSS database	Weighted centroid method, k-Nearest Neighbors (kNN)	Library; office open space	WC (4.43-4.88m);	105 (4, 12, 20dBm)	The database needs to be updated to include other location and collection orientation.
[22]	Trusted-ranges model	Trusted-ranges model	8x10 m^2, lobby		4 (4dBm)	Further investigation on interference cause by obstacle.
[30]	Random forest and particle filter	Multi-fingerprinting	14x18 m^2,	1.9~2.3m (RF) 1~1.4m (PF)	6	The method achieves high accuracy with low cost. Application at large indoor scenes is possible.
[31]	Calibration	Trilateration weighted Centroid, classic LSE, improved LSE	5x5 m^2, testbed	0.2 to 0.35m	4(4dBm)	The model achieves high accuracy for static device only. Dynamic devices and tracking application need further investigation.
[32]	Kalman Filter	Fuses Trilateration	44x17 m^2, corridor	2.75m	10	Specific human model and fusion approach need further investigation.

3. Methodology

3.1. Optimization Technique

In this work, PSO approach as an optimization problem is implemented for positioning BLE beacons, with an aim to ensure that the position of any mobile device in the indoor environment can be tracked via radio frequency distance measurement and trilateration method. Adoption of PSO algorithm in IPS system has attracted considerable attention due to high location accuracy with minimal computational complexity. It involves few parameters, thus relatively straightforward to be implemented than other methods, such as genetic algorithm (Xue et al., 2009). The PSO algorithm locates the BLEs based on intelligent particles which lead to an efficient and reliable localization approach. It is also more flexible for a temporary map generation, which requires less memory for the same accuracy as fingerprinting method (Zhang et al., 2009).

PSO was introduced by Kennedy and Eberhart in 1995 as a population-based metaheuristic for a single objective optimizer. Numerous works had been carried on PSO from robotics (Eberhart and Hu 1999), power distribution planning (Mohamad et al., 2013), biomedical optimization (Ibrahim 2012; Singh et al., 2012; Sun et al., 2006), wireless sensor networks (Rappaport 2001), and financial planning (Zhou 2017). PSO searches for an optimal solution within a search space by updating the particles' velocities and positions. Particle ith's velocity and position at dth dimension in the tth iteration, $v_i^d(t)$ and $x_i^d(t)$ are updated using the following equations.

$$v_i^d(t) = \omega v_i^d(t-1) + c_1 r_i^d(t)(pBest_i^d(t) - x_i^d(t-1)) + c_2 r_2^d(t)(gBest^d(t) - x_i^d(t-1)) \quad (1)$$

$$x_i^d(t) = x_i^d(t-1) + v_i^d(t) \quad (2)$$

The velocity update can be categorized into three parts, momentum, particle's nostalgia, and social influence. In the equation (1), ω is inertia weight. The inertia weight controls the particle's search momentum. Linearly decreasing inertia is often adopted to encourage exploration in the earlier phase of the search and facilitates fine tuning towards the end. Two learning factors, c_1 and c_2 are used in the equation. Usually, both learning factors are set to be equivalent to balance the influence of particle's own experience and swarm's experience. The particle ith's best experience up to tth iteration is represented by $pBest_i^d(t)$. Whereas, the best solution found by the swarm is; $gBest^d(t)$. PSO is a stochastic algorithm, $r_1^d(t)$ and $r_2^d(t)$ are two random number ranging from [0,1]. They are independent of each other. Particle's position is updated using Equation (2).

```
Random initialization of particles
While not stopping condition {
        Particles fitness evaluation
        Update pBest & gBest
        Update velocity & position
}
Report the best found solution
```

Fig. 1: PSO pseudocode

The flow of the PSO algorithm is shown in the pseudocode of Figure 1. Every iteration starts with particles' fitness evaluation prior to the $pBest$ and $gBest$ update. The velocity and position are updated after these steps. In the optimization of beacons' installation problem, which is considered here, each of the particles' positions represents the locations to install the beacons. In this project, the beacons are to be installed at the wall of each corridor. Meanwhile, the evaluation of particles' fitness depends on the problem to be solved, where we wanted to ensure that the position of any mobile device in the corridor can be tracked via trilateration method. Therefore, the device must be within sensing range; r of three BLE beacons. Hence, to ensure full coverage a BLE beacon must be within distance of $< 2r$ from at least two other BLE beacons. The value of r can be determined by taking into consideration the height of the beacon with respect to the floor and also the beacon's transmission/reception range. Hence, in this work the fitness function is formulated as below:

$$pCov_{bk} = \begin{cases} 0.5 & if\ dist_{bk} < 2r \\ 0 & otherwise \end{cases} \tag{3}$$

$$Cov_b = \begin{cases} 1, & if\ 1\ if \sum_{k=1} pCov_{bk} \geq 1 \end{cases} \tag{4}$$

$$fitness_i = \frac{\sum_{b=1}^{no.of\ beacons} Cov_b}{no.of\ beacons} \tag{5}$$

In Equation (3) the partial coverage of beacon b by beacon k, $pCov_{bk}$ is set to 0.5 if the distance between the two beacons is lesser than $2r$. The beacon b is fully covered if its total $pCov_{bk}$ is equal to or more than 1 as shown in Equation (4). The fitness of the beacons position proposed by particle ith, $fitness_i$ is finally calculated using Equation (5).

3.2. RSSI Method

RSSI measurements are conducted to examine reduction of power received as the receiver moves away from transmitter. The distance between BLE nodes and mobile phone can be computed and estimated by applying log-distance path loss model. Using path loss models, the PSO localization method generates fingerprints for all particles in the swarm which correspond to campus navigation map (Zhang et al., 2009).

3.3. Propagation Model

RSSI measured the energy power level can be received by a user's device from access point. Log-distance path loss model (Faragher and Harle 2014) is applied to estimate the distance between known BLE position and the smartphone Bluetooth device. The theoretical model is shown in Equation 6.

$$RSSI(d) = RSSI(d_0) + 10n\log(\frac{d}{d_0}) + X_\sigma \tag{6}$$

where RSSI (d) is the RSSI when the distance between beacons and smartphone is d, d_0 is the reference distance, n is the path loss coefficient related to the environment and X_σ is Gaussian distributed random variables. For actual localization measurement, d_0 is 1m and X_σ is omitted. Therefore, a simplified propagation model is given as follows:

$$RSSI(d_0) = RSSI(d) - 10n\log(\frac{d}{d_0}) \tag{7}$$

The distance can be estimated according to Equation 8 and the coordinate is determined by trilateration approach, in which three or more beacons are considered to figure out the position of a blind node.

$$d = d_0 \cdot 10^{\left(\frac{RSSI - RSSI_{d_0}}{10 \cdot n}\right)} \tag{8}$$

Trilateration technique is adopted to calculate an unknown position by referring to three known points. Considering three BLEs are used, namely A, B and C, the distance is measured from communication device to the three known BLE A, B and C position, based on measured RSSI value. To calculate the exact position of the communication device, Equation 9 need to be solved.

$$\begin{aligned} d_a{}^2 &= (x - x_a)^2 + (y - y_a)^2 \\ d_b{}^2 &= (x - x_b)^2 + (y - y_b)^2 \\ d_c{}^2 &= (x - x_c)^2 + (y - y_c)^2 \end{aligned} \qquad 9)$$

3.4. Experiment

This section describes the RSSI measurement to examine the localization accuracy based on optimum BLE position using the PSO algorithm, as described in Section 3.1. In this case, the beacons broadcast at -12dBm transmitting power. Minimum reception signal of -110dBm is required to establish communication between mobile phone and BLE. This corresponds to the maximum coverage area.

The system is implemented in such a way that, location tracking involves RSSI measurement using trilateration. It can operate using users' terminals, such as Bluetooth without interaction with middle server. In addition, it is important to consider the system is able to function well in concurrent multi-users accessing signals from BLE, while ensuring no privacy issue occurred due to users' self-positioning.

The model is applied to the in-building foyer, as described in Table 2. The foyer is surrounded by concrete and glass wall, with a pathway about 10m wide between the walls. Due to large area, it is expected that achieving perfect results would be challenging. Note that penetration between floors is not modelled here, as the simulation and measurement is conducted in one floor only.

Table 2: Description of RSSI measurement zone

Zone	A	B	C	D
Environment	In building foyer			
Blockage	Glass wall	Concrete wall	Glass wall	Concrete wall
Number of beacons	16	14	14	20
Number of smartphones	1			
TX powers (dBm)	12dBm			
Height of the area	6m			

A unique ID is assigned to each the fix BLE beacon for tagging purposes. BLE is mounted on the wall at 1.7m height. The BLE-enabled devices sense the signal from the beacon and notify the adjacent devices on their existence. The routing mechanism in an indoor location is determined by measuring the position of BLE. To execute this project, the position of BLEs is first predicted using PSO.

After the installation, the RSSI from radio beacon devices are recorded from a smartphone Bluetooth device as the pedestrian walked in the pathways. In the end, based on the current geo-coordinates of the smartphone, BLE distance can be estimated.

4. Result

4.1. BLE Beacons Placement using PSO

The solution proposed here was tested for the installation of 30 BLE beacons for an indoor navigation system at the ground floor of the Faculty of Engineering and Technology, Multimedia University. The indoor environments are divided into four corridors to represent LOS and NLOS scenarios namely Zone A, Zone B, Zone C and Zone D. The floor plan is shown as in Figure 2.

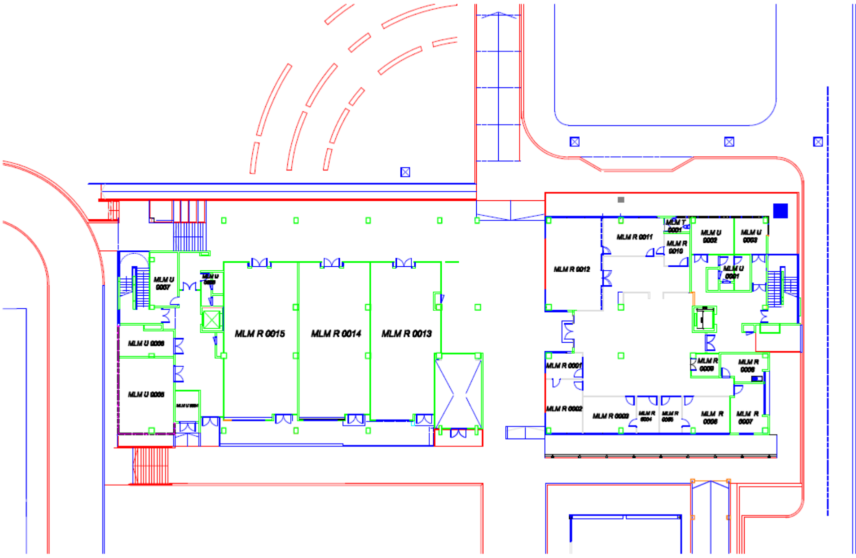

Fig. 2: Floor plan

The PSO was run with 20 particles for 100 iterations and managed to optimize the placement with an estimated coverage of 86.67%. This is shown in Figure 3. The locations of the beacons and navigation system are shown in Figure 4 and Figure 5, respectively. The red circles show the position of the beacons. Using the positions determined by PSO the beacons were placed on the balcony of the ground floor of the Faculty of Engineering and Technology, Multimedia University. The suitability of this solution is then validated using RSSI as discussed in the following section.

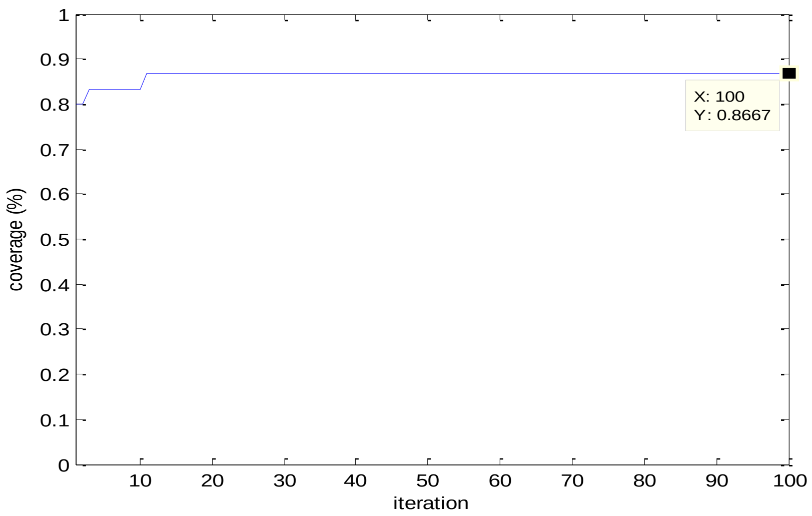

Fig. 3: Fitness of PSO solution

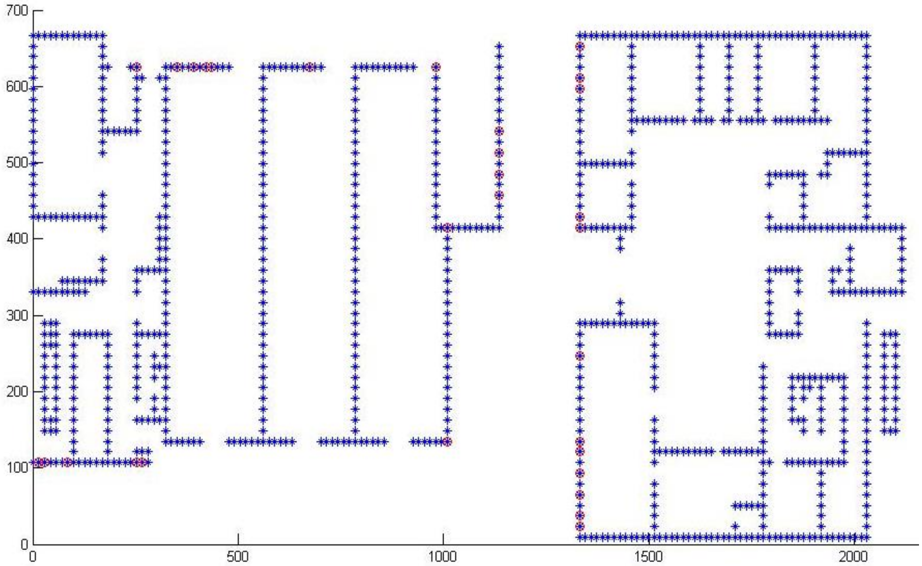

Fig. 4: BLE beacons position proposed by PSO

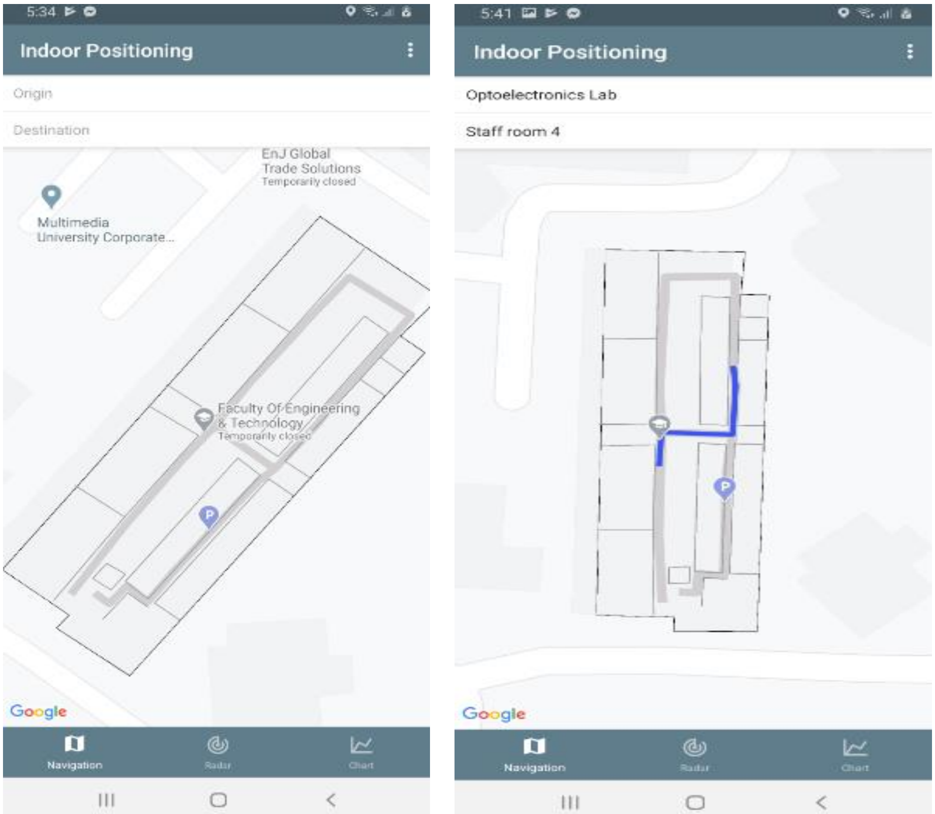

Fig. 5: Campus navigation system

The optimal positioning of BLE is determined with the aid PSO algorithm as described in Section 3.1. In this section, the analysis is focused on the use of the RSSI and the log-distance path loss model of the entire IPS simulation. The result described here, is basically obtained from BLE RSSI measurements collected from BLE points. Path loss dependence on the antenna heights is insignificant as the height is similar and closed to the environment.

In order to validate the accuracy of the developed positioning algorithm based on PSO, path loss and trilateration, RSSI data were recorded for each of the consecutive zones with a smart phone device. The distance between BLE is 5 meters and 15 meters for adjacent and opposite sides of the foyer, respectively.

Figure 6 represents RSSI measurements after 30s of walking. The plot of RSSI quantifies the placement of BLE using PSO and trilateration as relate to the actual coverage with respect to the distance between smartphone and beacon as an access point. In this case, minimum reception signal of -110dBm must be detected which imply communication between mobile phone and BLE is successfully established. As the signal spread, it is noticeable the signal strength decay in a random behavior.

The finding reinforces the result obtained (Obeidat et al., 2021), whereby RSSI-distance relationship is not necessarily linear.

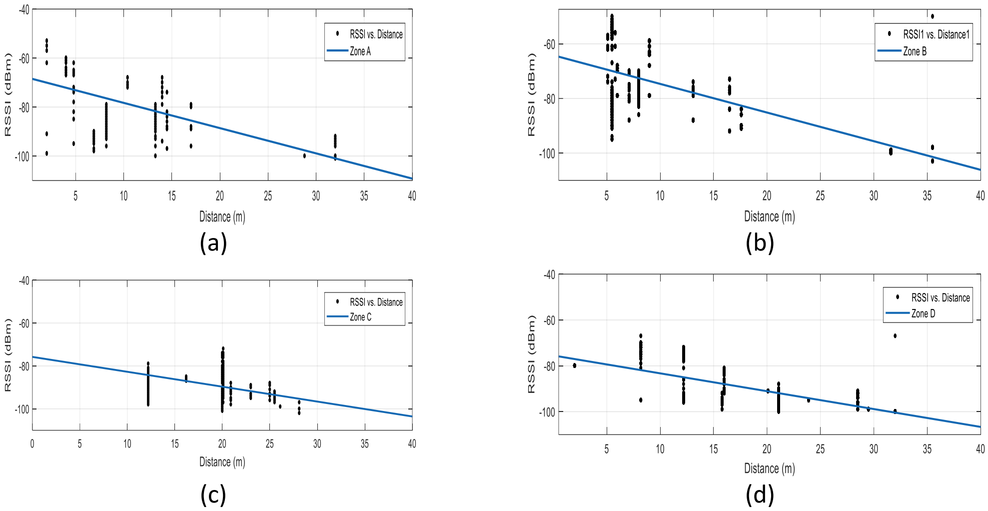

Fig. 6: RSSI measurement at (a) Zone A, (b) Zone B, (c) Zone C and (d) Zone D

It can be observed that relatively good and stable signals are received at Zone B as depicted in Figure 6. The minimum average RSSI is more notable in Zone C and Zone D. This difference is expected as the zone is slightly blocked by the concrete walls. Hence, the observed decay with distance fits that of a signal reflected through a rough medium. As pointed in (Parsons 2000), wall roughness introduces additional attenuation to the RF signal and smoothness to the power distribution curve, which greatly interferes with the stability of BLE signal. Therefore, it is important to place the BLE at a certain distance from the corner.

Also, obstructions such as doors, tables and chairs, might cause reflection and scattering. Hence, the presence of various objects typically causes several copies of the transmitted signal to reach the receiver via multiple paths. The signal might reach the receiver in or out of phase. The receiver will be having stronger signal if the components of waves are received in phase. However, if out-of-phase signals are received, they tend to cancel each other, subsequently producing a weak or fading signal. This indicates reflecting surface has a substantial effect on the BLE signal propagation. Moreover, the propagation characteristics change as the terminal moves from BLE to other BLE and from time to time.

The measurement demonstrates indoor signals suffer from strong and static and dynamic multipath distortion due to reflection from walls, granite rock floor and other blockages exist such as table and chairs. The maximum loss occurs at a distance of 25m due to the beacon transmit power that is insufficient to deliver the signal to the receiver. Particularly, at 2.4GHz, strong human body absorption, may deteriorate the signal up to 10dBm.

4.2. Model Validation

Two different approaches were used to evaluate the performance of the proposed positioning. Firstly, the model results were assessed based on the path loss data. Secondly, the accuracy of the proposed positioning is statically evaluated and compared using standard deviation and Root Mean Square Error (RMSE) as performance metrics. The approach, which is quite common in positioning applications is given by the following mathematical equations.

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(RSRP_m-RSRP_p\right)^2} \tag{10}$$

$$SD=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left|RSRP_m-RSRP_p\right|-\mu\right)^2} \tag{11}$$

Table 3: Performance

Zone	A	B	C	D
$RSSI_{(max)}$ (dBm)	-53	-50	-72	-67
$RSSI_{(min)}$ (dBm)	-101	-103	-102	-100
$RSSI_{(average)}$ (dBm)	-80.21	-77.02	-89.91	-89.58
Standard Deviation	12.73	12.647	6.009	8.684
RMSE	14.684	15.460	20.876	19.998
Path loss exponent	3.15	2.68	3.08	3.76

The resulting RMSE shown in Table 3, indicates a reasonable performance of the proposed positioning. The calculated RMSE is most likely due to a large signal deviation as a proportion of movement through a wide pathway. In addition, the signals from three BLEs do not always intersect at one point in trilateration approach and thus, ranging based on RSSI will produce errors in a distance. Accordingly, the positioning measurement on the ground floor proves to be complex and nonlinear, thus the obtained result is logical.

In view of the path loss exponent, it is observed that the path loss exponent n ranges from 2.68 to 3.76. The larger value of n in this case, is due to the presence of significant blockages that potentially block the signal.

5. Conclusion

This paper presents the implementation of PSO and trilateration method for a reliable and robust indoor positioning system. PSO which is simple and direct, is significantly useful at the initial stage to automatically extract the number and optimal position of BLE. By exploiting the information of RSSI with trilateration method, relevant prediction can be obtained. The accuracy of the model is validated using an experiment conducted on in-building foyer environment. It is found that, a larger RMSE in range of 14.68 to 20.88 is recorded, with path loss ranging between 2.68 to 3.76. It can be seen, the indirect signal path between BLEs and mobile devices can impact localization accuracy.

Future works will be extended to focus on the reduction of error due to multipath and interference caused by moving objects using larger dataset of measurements. As the algorithm demonstrates valid results, therefore, consideration of filters to be applied in processing the data will be a subject of future work. The applicability of the test model will be tested to different datasets and environments and comparison compared with the other optimization algorithms.

Authors' Contributions

Conceptualization, NZAR and NAAA; methodology, NAAA; validation, CTK and NRR; formal analysis, NZAR, investigation, CTK and NRR; writing-original draft preparation, NZAR and NAAA; writing-reviewing and editing, FSA and RA; visualization, NAAH, supervision, NZAR and NAAA; project administration, NZAR and NAAA; funding acquisition NZAR and NAAA.

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