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Path Loss Exponent Estimation for Indoor Wireless Sensor Positioning

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Abstract

Rapid developments in wireless sensor networks have extended many applications, hence, many studies have developed wireless sensor network positioning systems for indoor environments. Among those systems, the Global Position System (GPS) is unsuitable for indoor environments due to Line-Of-Sight (LOS) limitations, while the wireless sensor network is more suitable, given its advantages of low cost, easy installation, and low energy consumption. Due to the complex settings of indoor environments and the high demands for precision, the implementation of an indoor positioning system is difficult to construct. This study adopts a low-cost positioning method that does not require additional hardware, and uses the received signal strength (RSS) values from the receiver node to estimate the distance between the test objects. Since many objects in indoor environments would attenuate the radio signals and cause errors in estimation distances, knowing the path loss exponent (PLE) in an environment is crucial. However, most studies preset a fixed PLE, and then substitute it into a radio propagation loss model to estimate the distance between the test points; such method would lead to serious errors. To address this problem, this study proposes a Path Loss Exponent Estimation Algorithm, which uses only four beacon nodes to construct a radio propagation loss model for an indoor environment, and is able to provide enhanced positioning precision, accurate positioning services, low cost, and high efficiency.

Keywords: RSS, path loss exponent, indoor, position

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1. Introduction

The concept of ubiquitous computing has brought changes to the living environments. With advancement in wireless technology, sensor precision, miniaturization, and computer chips, wireless sensor networks have grown in popularity. Many wireless sensor network technologies have been widely applied in daily life, and applications for positioning people and objects have been extensively studied. Spatial positioning can help users to identify orientation and provide related services according to the users' position; thus, users can enjoy the convenience and practicality of ubiquitous computing.

Positioning systems can be used in both indoor and outdoor environments. GPS is the most commonly used method in outdoor environment positioning, and is widely applied in many fields [1][2]. However, for indoor environments, GPS cannot be fully functional due to LOS limits. An Indoor Positioning System (IPS) is difficult to implement due to complex indoor settings and high precision demands. Common methods adopted for wireless positioning systems include RSS, angle of arrival (AOA), time of arrival (TOA), and time difference of arrival (TDOA). This study employs the RSS approach to calculate the coordinates of test points. The RSS approach uses a radio propagation model to describe the distance attenuation with path loss. However, a radio propagation loss model for the environment must be constructed first in order that the wireless receiver can use the propagation loss model to estimate the distance between the test points and beacon nodes, according to the received signal strength. Since a wireless signal is transmitted as an electromagnetic wave, phenomena, such as reflection, refraction, diffraction, scattering, and multipath, could easily occur in complex indoor spaces [3][4], resulting in intermittently strong signals. For example, indoor furniture, articles, and movement would affect the radio propagation in the room, thus, the received signal strength would be different from that of the free space propagation. Such differences would cause errors in estimating the difference between the test points and beacon nodes, and hence, affecting positioning accuracy. To address this problem, this study proposes a Path Loss Exponent Estimation for Indoor Wireless Sensors Positioning System, which only requires four beacon nodes to construct a indoor environment radio propagation loss model. It can improve positioning accuracy, and provide accurate positioning service with low cost and high efficiency.

The remainder of this paper is organized as follows. Section 2 is the literature review, and explains the current indoor environment positioning services and related issues; Section 3 introduces the positioning system framework; Section 4 describes the framework of a Path Loss Exponent Estimation Algorithm; Section 5 discusses the experimental data and results; and Section 6 proposes conclusions and suggestions for future studies.

2. Related Work

To date, there are four positioning models for positioning services in wireless sensor network environments [5][6][7][8]: AOA, TOA/TDOA, the hybrid angle and time of arrival, and the RSS approach. The AOA approach uses the angle of the mobile device signal detected by an antenna to achieve accurate positioning; the working principle is as follows: the data are measured by the directional antenna or antenna array, which then send to the blind nodes. The beacon nodes receive source directions from signals emitted by the blind nodes, or the probable direction of the blind node position. The receiver uses this data and known coordinates to calculate the blind node coordinates. The TOA/TDOA approach obtains the relative distance between the receiver and the sender from the time required to transfer the wireless signal. The wireless signal propagation time between the blind node and beacon node is measured, then multiplied by the propagation rate (electromagnetic waves propagate like the velocity of light), in order to estimate the distance between the blind node and beacon node. The data are then used to estimate the blind node coordinates. The hybrid angle and time of arrival approach combines the two approaches mentioned above, this couples time difference and angle of received signal determine the blind node position. The RSS approach employs a radio propagation model to describe the distance attenuation with path loss; the strength of the signal received by the blind node indicates the RSS value. The received RSS value is substituted into the radio propagation model, which derives an estimated distance from the transfer point and estimates the blind node coordinates. Among these four approaches, TOA/TDOA achieves positioning based on estimating the time difference between the sender and receiver, with fast wireless network transmission rates and insignificant time variables. However, if the time variation is unknown the positioning would be erroneous, and thus, requires extra hardware for time synchronization in order to reduce the distance errors due to errors of time differences. AOA also requires an additional antenna array for positioning. Compared to TOA/TDOA and AOA, the RSS approach does not require additional positioning hardware for the radio propagation model. In terms of cost, the RSS approach has the lower cost, as compared to the other three approaches, and it is more suitable for indoor environments.

Moreover, the other three approaches are vulnerable to the multi-path problems common in indoor environments, while the RSS approach can predict changes in signal strength displacement and the dependent variables of the obtained positions, thus, have higher measurement accuracy [9][10][11]. Based on the above, this study applies the RSS approach as the basic algorithm framework, which uses the radio propagation model to describe distance attenuation with path loss, and the radio propagation model to convert distances from senders when the receiver receives a sent RSS. The main parameter of the radio propagation model is the PLE, which is an attenuation exponent for the received signal, as the radio propagation distance is increased, thus, PLE varies with its environment [12]. In terms of indoor positioning, obstacle objects are a key factor. As indoor environments contain various furniture or decorations, and such articles have different absorptivity of signals and are often arranged irregularly, the wireless signal is easily absorbed when propagating in a room. As a result, positions and materials of articles should be considered when estimating indoor positions based on signals. Moreover, 70% of the human body consists of water; and therefore, absorbs wireless signal. Signal variations would be greater when used in a larger population or involving frequent human movements. Since obstacles absorb signals, many studies on positioning have treated the PLE as a constant; hence, the PLE is often not reflected in real environments, which may cause serious errors in complicated indoor environments. Many current studies have explored the above problems, for example, [13] proposed two methods to estimate PLE, which are the Cayley-Menger determinant and the Pattern matching approach, both of which assume that the loss factor of each link is the same. Whereas, [14] set up beacon nodes in a grid-based manner, and assumed that each link had a different PLE. The algorithm contains two steps: 1) Step 1: obtain the PLE of each link, and utilize the maximum and minimum PLE to position the region of the blind node; 2) Step 2: utilize related data derived from Step 1 to estimate the blind node position. [15] added Path-loss exponent estimation nodes (PLE node) to measure the environment of the PLE, and proposed two methods: 1) average the PLEs of PLE nodes in an environment to obtain the environment PLE, and 2) choose the PLE nearest to PLE node for blind nodes, and then, use a triangulating approach to estimate the blind node position. In the grid-based method [14], eight becan nodes are required to get the more accuracy. In contrast to other methods, [15] needs one more PLE node to get PLE values in the experiment environment.

This study uses four beacon nodes to construct indoor PLE among the beacon nodes. In the other words, the current PLE could be estimated dynamically according to the environments. By combining PLE and a radio propagation model, the distance between the blind node and beacon node can be calculated, and then, a polygon approach is used to estimate the blind node position.

In compliance with the two methods aboved, the proposed mechanism in this study could reduce the cost and improve precision of estimating the blind node positions.

3. System Structure

The system framework of this study is shown in Figure 1, which contains a server, a base station, beacon nodes, and blind nodes [16]. Blind nodes are the positioning nodes in the system, beacon nodes are the reference nodes for positioning, for which the actual coordinates of the beacon nodes in the system are shown in Figure 1, and are used as reference for positioning. The base station forms a wireless sensor network and feeds the relative RSS values detected by the beacon nodes and blind node back to the server. The sensor nodes of the 8-bit processors used in this system are not suitable for mathematical operations, as frequent execution of such operations would lead to higher power consumption. Hence, the sensor nodes of this system are only responsible for collecting position-related information, which is sent to a server for operations. The server receives the related RSS values, and then uses the algorithm proposed in this study to accurately estimate the blind node position in the system.

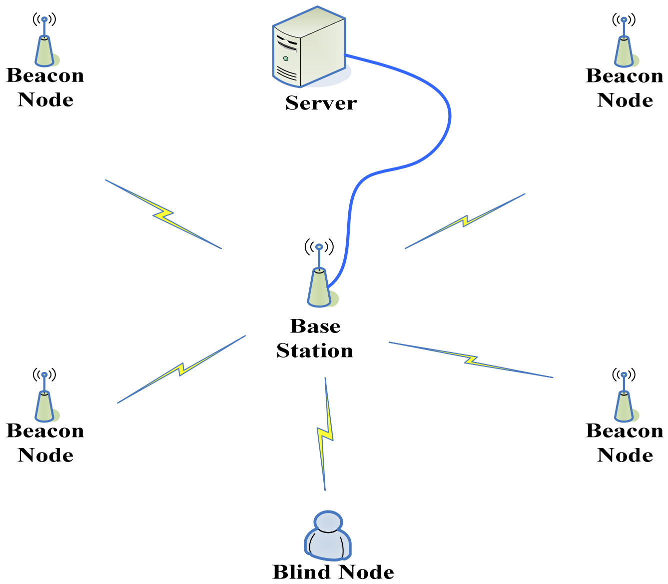

Fig. 1. System Architecture.

As shown in **Fig. 1**, when a blind node sends a positioning request to the base station, the station transfers the initial command to the beacon nodes by broadcasting. When the beacon nodes receive an initial command, they would detect the RSS propagated from other beacon nodes, and transfer the collected RSS to the server via the base station. The server employs the algorithm proposed in this paper to compute the PLE of the environment of the beacon nodes. After the initial stage, the base station sends a positioning command to the blind node, which receives the command, collects the RSS of each beacon node, and feeds this data back to the server via the base station. When the server receives the blind node feedback RSS, it employs the proposed algorithm to estimate the PLE coordinates of the blind node in the environment. The experiment confirmed that, the proposed algorithm can estimate blind node coordinates, with improved accuracy and low cost.

4. Path Loss Exponent Estimation Algorithm

4.1 Radio Model

As shown in Eq.(1), in the wireless transmission propagation loss model [18][19][20], PL(d) denotes the strength of the signal, which the wireless receiver receives from d meters distance from the wireless sender (dBm), while d0 denotes the reference distance, which is set to 1m in this study; denotes the path loss exponent, and the attenuation index of the received signal varies with the environment, as the wireless transmission distance increases; denotes the shadow fading effect, which is a Gaussian random variable with a mean of 0 and standard deviation of ; and is related to the obstacle signal loss. The measured received signal may differ due to different obstacles, even if the propagation distance is the same and emitted signal has the same strength. Eq.(2) is derived from Eq.(1), and is used to obtain the path loss exponent, n denotes the number of measurements of a single connection. When a receiver receives an RSS from a wireless sender, Eq.(1) is used to estimate the distance between the receiver and sender, d.

$$PL(d) = PL(d_0) - 10\alpha \log(\frac{d}{d_0}) + X_\sigma \tag{1}$$

$$\alpha = \frac{-\sum_{i=1}^{n}(PL(di) - PL(d_0))}{\sum_{i=1}^{n}10(\log di)} \tag{2}$$

4.2 Estimation Algorithm

This section introduces a Path Loss Exponent Estimation Algorithm, as shown in **Fig. 2**.

(I) The Initialization state collects the mean RSS data between the beacon nodes in an environment, and feeds it back to a base station. After establishing the number of beacon nodes, and their actual coordinates, the server sends out an Initial command to the base station, which sequentially transfers the command to each beacon node by unicast. The GetRSS command is broadcasted to other beacon nodes after the receipt of the initial command. When the beacon nodes receive a GetRSS command, the mean RSS between the nodes is replied (average of 100 times), then, the mean RSS of other beacon nodes is fed back to the base station, when base station collects all of the mean RSS data between the beacon nodes in an environment, base station will send it to the server as shown in Fig. 3.

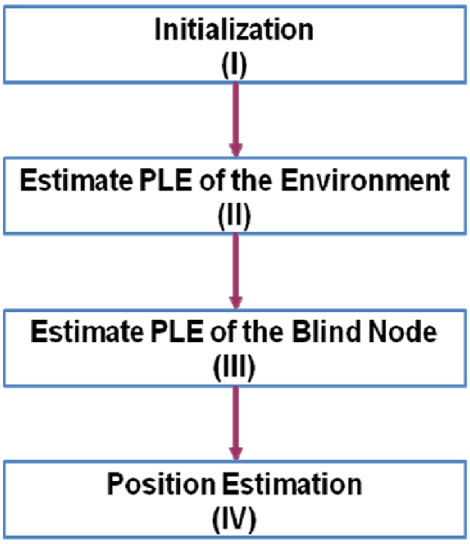

Fig. 2. Algorithm Flowchart.

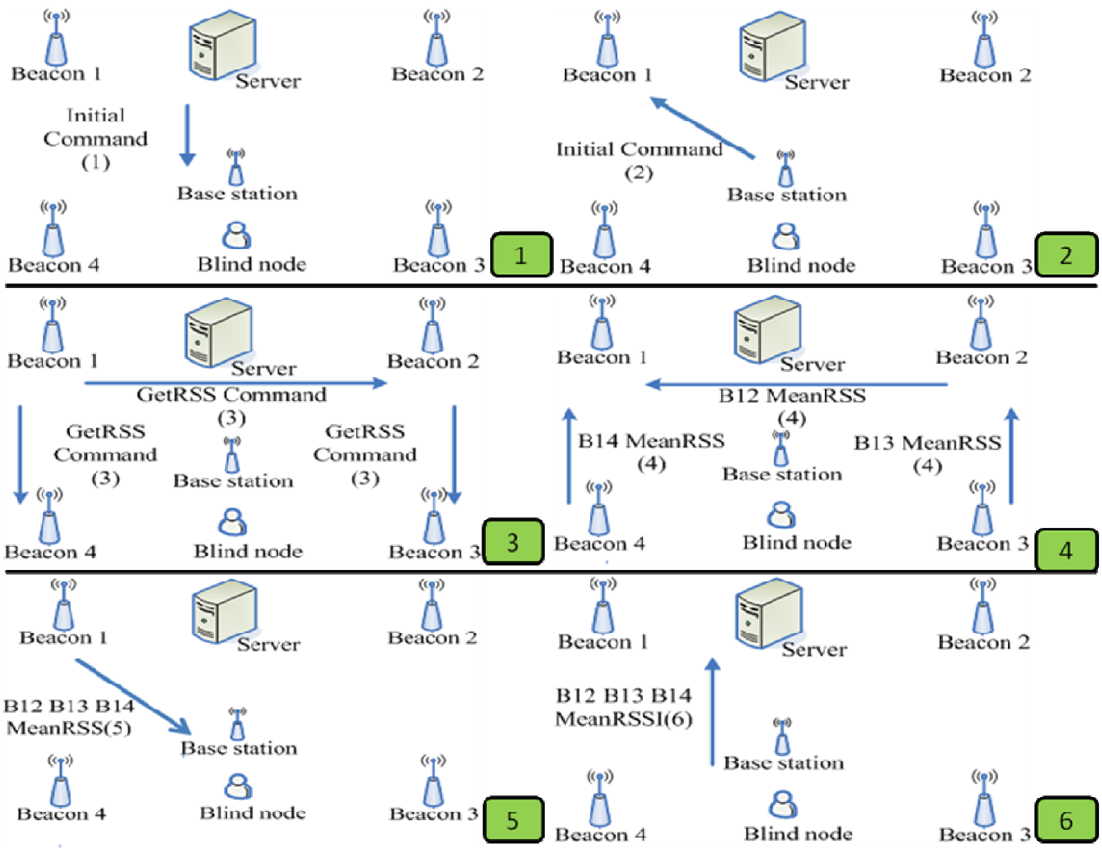

Fig. 3. Initialization State Interaction Figure.

(II) Estimate the PLE of the environment: Based on the mean RSS data between the beacon nodes, as collected in step (I), the Server uses Eq.(2) to compute the PLE between the beacon nodes, and then uses this information to analyze the PLE distribution in an environment, as shown in **Fig. 4**.

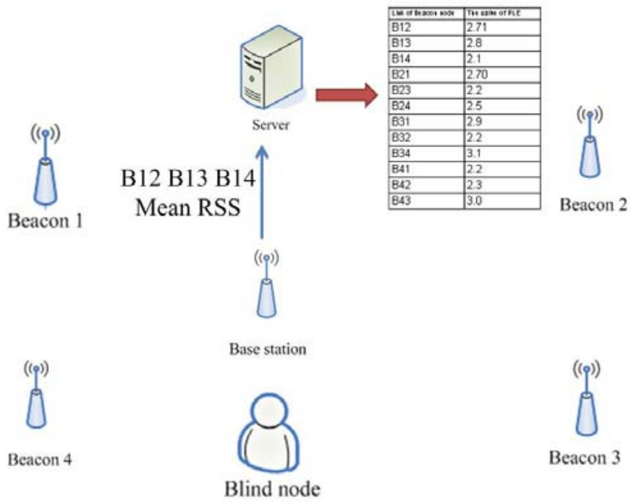

Fig. 4. Estimate the PLE of the Environment State Interaction.

(III) Estimate the PLE of the blind node: PLE distribution in an environment, as obtained in step (II), is used to estimate the PLE of blind node locations. The server first sends a Blind_Initial command to the base station, allowing the base station to transfer a Blind_Initial command to the blind node by unicast. Upon receipt of the command, a Get_Position_Info command is broadcasted to each beacon node. When the beacon node receives the Get_Position_Info command, the mean RSS between the blind nodes (average of 100 times) and actual coordinates are fed back to the blind node, which feeds the information back to the server via the base station. The server sorts the RSS values between the blind and beacon nodes in a descending order, and then, takes the two largest RSS values and determines the corresponding beacon nodes. Based on the results obtained in step (II), the Server can obtain the PLE between such two beacon nodes and average the two PLEs. This PLE is set as the PLE of the blind node environment, as shown in **Fig. 5**.

(IV) Finally, according to the blind node environment of the PLE, as obtained in step (III), and the mean RSS data between blind nodes and each beacon node, the server uses Eq.(1) to obtain the distance between blind nodes and each beacon node. The Polygon Method is then employed to estimate the coordinates of the blind Node.

5. Experiment and Result

In this experiment, CC2431 demo boards were used as beacon nodes and blind nodes. The survey site was an office environment [17], as shown in **Fig. 6**. The beacon nodes are set from 3 to 10, and their deployment is shown in **Fig. 7**, where the (a) number of beacon nodes is 3, while (b), (c), and (d) are the setup methods in the order of 4, 5, and 9 beacon nodes, respectively. Table 1 shows the experimental parameters. In this site of an 18m x 18m office, 10 locations were set, and their coordinates were measured. The blind nodes were placed at those 10 locations, and three implemented positioning algorithms were employed for estimations.

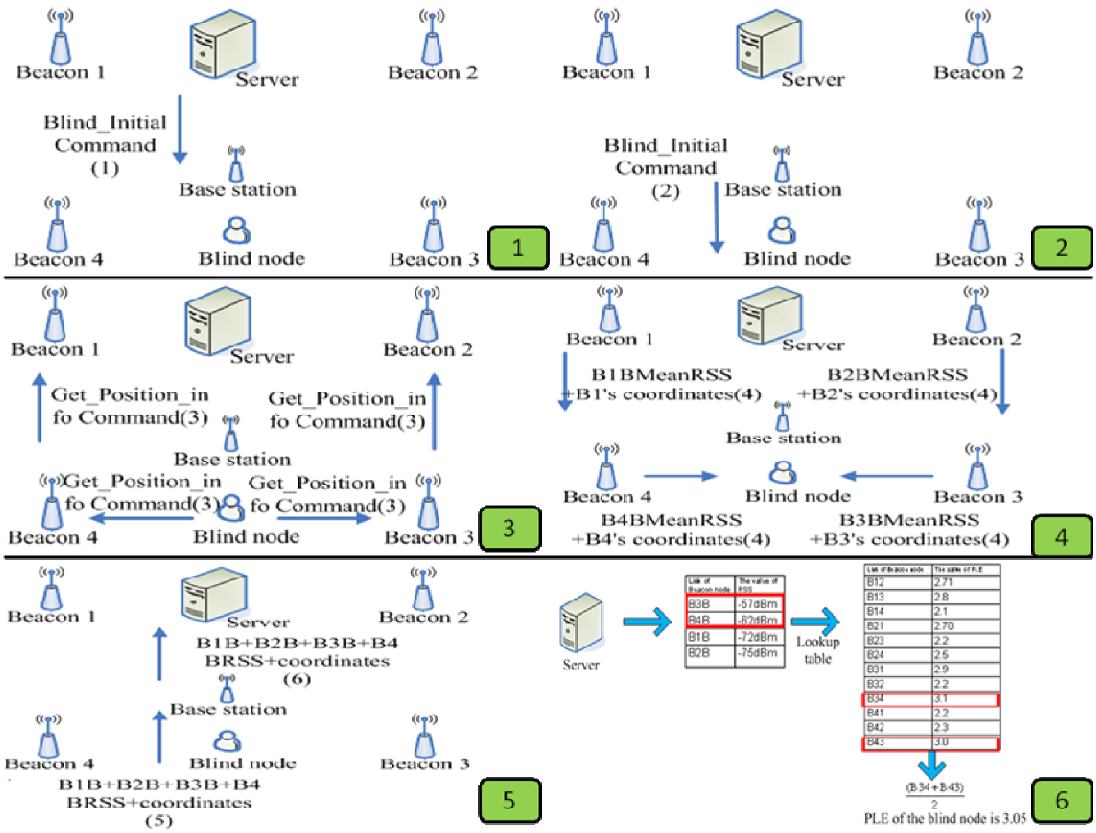

Fig. 5. Estimate the PLE of the Blind Node State Interaction.

In the same environment, the blind node at the same location can be positioned using different shadowing factors, different PLEs, and different numbers of beacon nodes. Each location was measured 50 times; the result after 500 times of positioning was obtained. The estimated coordinates and actual coordinates were used to compute the Root Mean Square Error (RMSE). The simulation of different PLEs was based on different scenarios in an office environment, including the number of persons in the office, their movements, and object obstructions. PLE values of the above scenarios were measured, and used to simulate the variable PLEs for positioning. This experiment employed three positioning methods: 1) the fixed method, which is the normal fixed PLE method, according to [18], the PLE of the in building line-of-sight environment, in this study, is defined as 1.8.; 2) the main method, using [15], regards the beacon node as a PLE node in order to estimate the environment of the PLE; and 3) the proposed method of this study.

5.1 Experiment Parameter

Table 1 shows the parameters in this experiment. The experiments were performed 500 times in the 18m x 18m field area of this environment. The parameters of radio output power and RSS detection threshold are assigned based on the hardware characteristics of CC2431. Except for the value less -93dBm initiated with RSS detection threshold, we adopt all the measured receive sensitivity. In this paper, the radio output power is set to 0 dBm according to the maximum output of CC2431 without power amplifier.

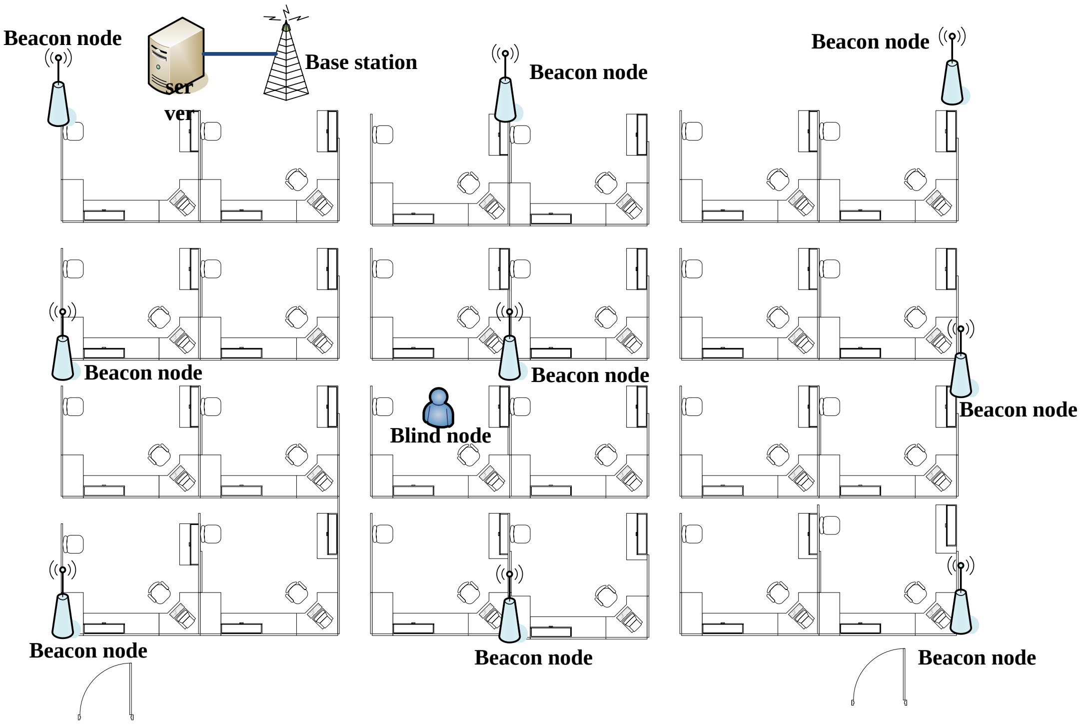

Fig. 6. Experiment Environment.

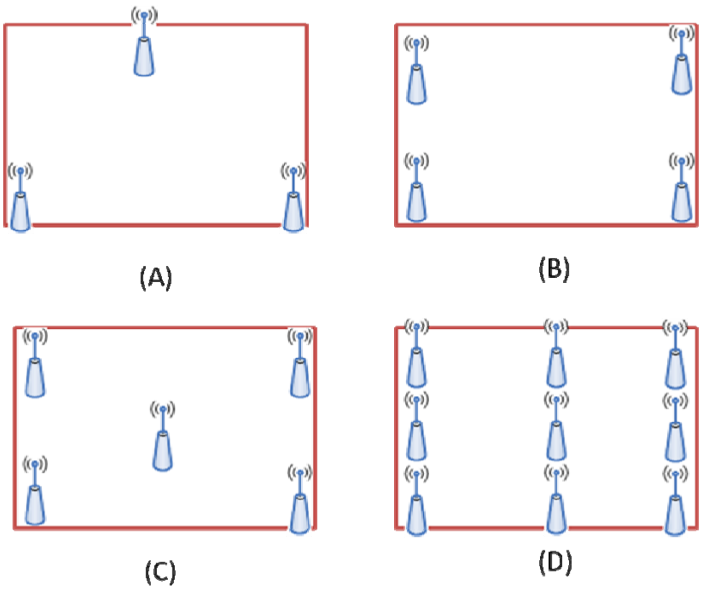

Fig. 7. Deployment of the Beacon Nodes.

Table 1. Experiment Parameters

Simulation parameter	Value
Size of sensor field	18m x 18 m(office)
Standard deviation	1~7dBm
One meter RSS P0	-45dBm

RSS detection threshold	-93dBm
Radio Output Power	0 dBm
Number of reference nodes	3~10
The number of experiments	500 times
The value of PLE (for fixed PLE method)	1.8

5.2 Results and Discussion

Fig. 8 shows the RMSEs measured by various numbers of beacon nodes, when PLE=3 and σ =2dBm. For the proposed method, when the number of beacon nodes is 4 and 8, respectively, the derived RMSEs differ insignificantly, indicating that if there are more than 4 beacon nodes, good positioning accuracy could be achieved. For the fixed method in the same environment, more beacon nodes lead to lower RMSE.

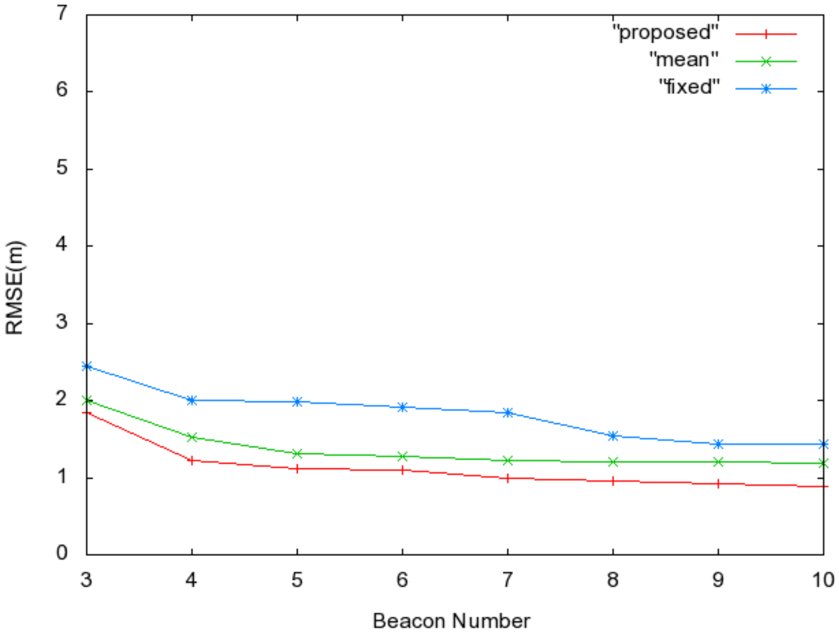

Fig. 8. RMSEs Measured by Various Numbers of Beacon Nodes (PLE=3 and σ =2dBm).

Fig. 9 shows the RMSEs measured using various numbers of beacon nodes, when PLE=4.5 and =6dBm. Compared with Figure 8, even in a variable environment unfavorable to RF transmission, when the number of beacon nodes is 4 and 8, respectively, the RMSEs obtained by the proposed method differ insignificantly. As shown in **Fig. 9**, when the number of beacon nodes is 4, the RMSE for the proposed method is about 1.87m. In comparison with the proposed method, when using the main method and the fixed method, and the numbers of beacon nodes are 8 and 9, respectively, RMSE falls below 2m. According to Figures 8 and 9, the proposed method can employ the least number of beacon nodes to achieve good accuracy, realizing the goal of low cost and high accuracy.

Fig. 10 shows the RMSEs measured in the case of 4 beacon nodes, in a variable environment of PLE=4.5 and the variable. As compared with the main method and the fixed method, RMSE for the proposed method in variable environment could reach a maximum of 2.13m, and minimum of 1.13m, indicating that accuracy can be maintained in a variable environment. Taking the fixed method for example, as increases, the RMSE becomes greater, and the maximum is 4.35m. For the main method, the result is generally between those of the proposed method and fixed method.

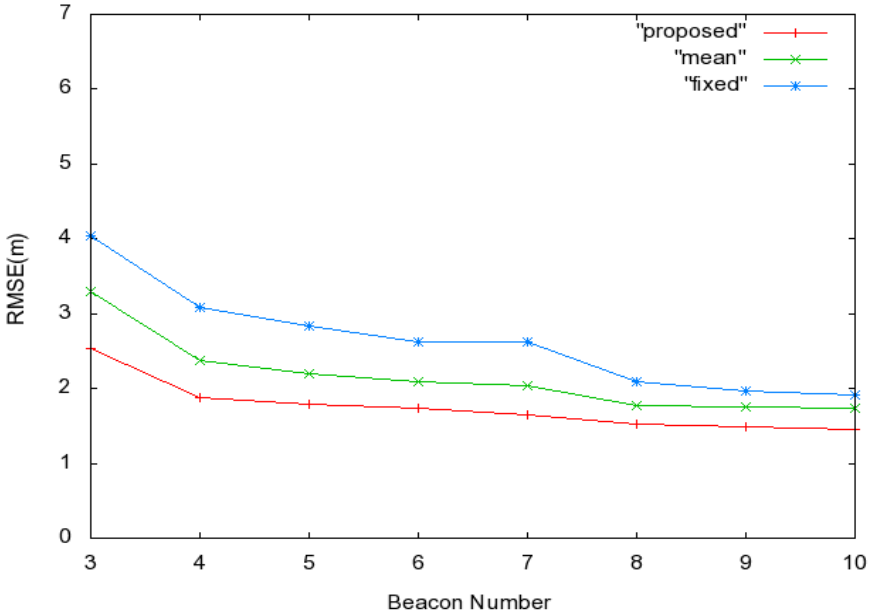

Fig. 9. RMSEs Measured by Various Numbers of Beacon Nodes (PLE=4.5 and σ =6dBm).

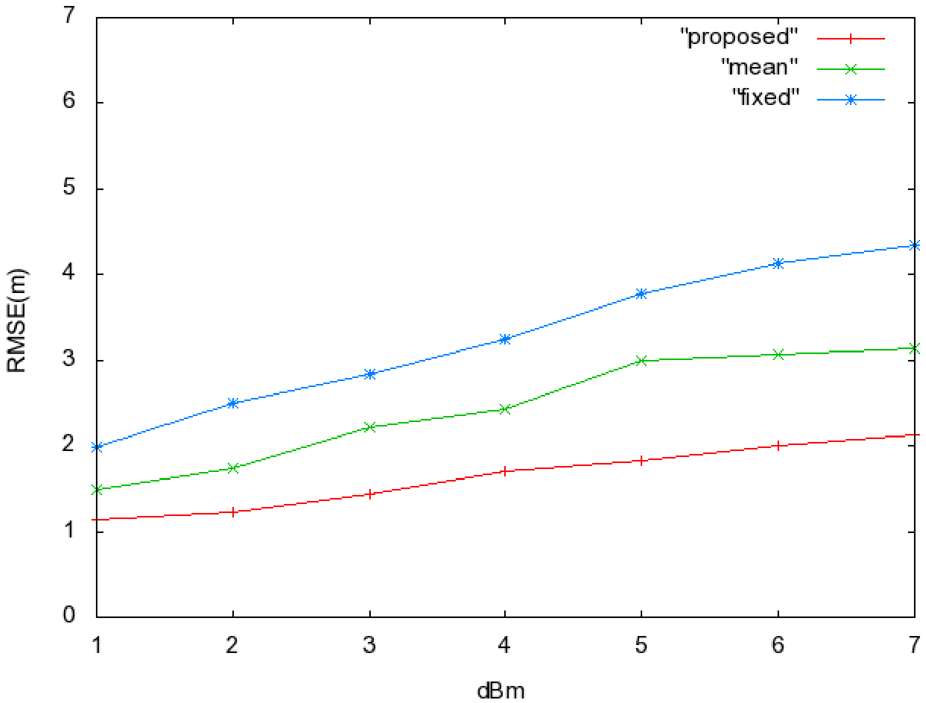

Fig. 10. RMSEs Measured by Variable (beacon nodes = 4).

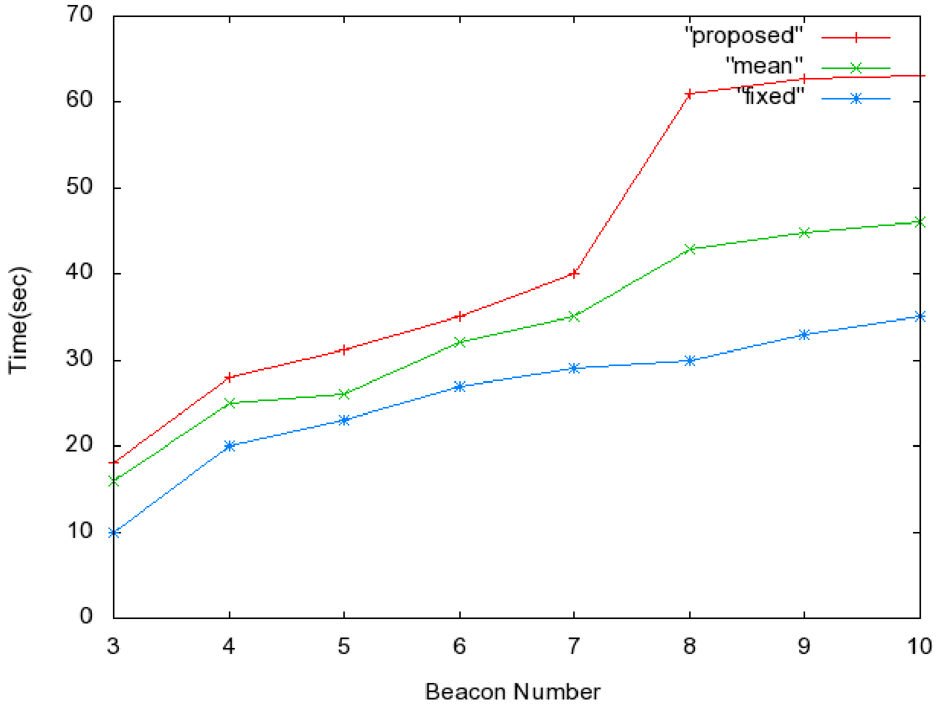

Fig. 11. Estimation Times by Various Numbers of Beacon Nodes.

By using the algorithm proposed in this paper, PLE can be obtained in real time and under different environments, while in cases of different numbers of beacon nodes, the required estimation times of the system would differ. For the proposed method, when the number of beacon nodes is 8, the required estimation time is 60.9s. For the main method and the fixed method, when the number of beacon nodes is 8, the required estimation time is 42s and 30s, respectively. Since the algorithm proposed in this paper has good accuracy, when the number of beacon nodes is 4, the proposed method system takes about 30s, which is close to the 25s of the main method, and the 20s of the fixed method, thus indicating good positioning accuracy, as shown in **Fig. 11**.

5. Conclusions

The RSS method may be influenced by environmental factors, and thus, cause errors in indoor positioning. The Path Loss Exponent Estimation for Indoor Wireless Sensors Positioning, as proposed in this paper, can estimate a environment PLE for variable environments, with the advantages of low cost and fast speed. The experiment proved that, the proposed algorithm can provide good accuracy, when the number of beacon nodes is 4, and system time consumption is about 30s. Maximal RMSE can reach 2.13m in cases of variable environments unfavorable to RF transmission, which is better than the 3.13m of the main method, and 4.35m of the fixed method. The proposed algorithm can provide accurate positioning services at a low cost, and be applied to digital homes and home care to achieve indoor positioning with only a few beacon nodes. These positioning services can provide better living quality and better medical service to users. Future studies will propose more accurate and faster positioning approaches at a low cost for various indoor positioning purposes, improve the performance of this algorithm, and provide more applications.

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