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Optimizing Node Localization in Wireless Sensor Networks Based on Received Signal Strength Indicator

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ABSTRACT In order to improve the precision of inside localization and optimize the allocation of node resources in wireless sensor networks (WSNs), an equal-arc trilateral localization algorithm based on received signal strength indicator (RSSI) is proposed from the perspective of increasing measurement precision and bettering beacon nodes layout. The algorithm adopts Kalman filter to filter the data collected from the best communication range, thus the disturbance problem of RSSI value can be tackled easily. By analyzing the changeable relationship between the communication distance and the RSSI, an optimal communication distance can be identified to satisfy the application requirements. In this paper, an equal-arc triangular beacon node layout model is established to ensure that the motion tracks of unknown nodes are always situated within an optimal communication distance to improve the measurement precision. The experimental results show that the proposed work increases the average location accuracy of the equal-arc triangulation layout model by 81%, 54%, and 48%, respectively, compared with the traditional square beacon model, the traditional equilateral triangle beacon model, and the improved equilateral triangle beacon model. In comparison with the traditional triangular layout, the equal-arc layout area coverage is increased by 23%.

INDEX TERMS Wireless sensor networks, RSSI, Kalman filtering, equal-arc triangular, particle swarm algorithm.

I. INTRODUCTION

Node localization plays an important role in wireless sensor networks(WSNs). Node localization in WSNs, especially in different scenarios, focuses on the accurate location in accordance with practical application requirements. For WSNs, in various fields, such as emergency situations, equipment monitoring, space exploration and smart home, the technology possesses the value of business research.

Location Based Services(LBS), such as navigation, Location Based Social Networking(LBSN) and tracking, are being widely adapted by people around the world [1]. Compared with the reliability, continuity and stability of outdoor localization, indoor localization in these aspects is relatively poor [2]. The indoor localization has higher requirements for accuracy in practicable application. In outdoor localization, the Global Navigation Satellite Systems (GNSS) are mostly used around the world: such as the US Global Location Systems(GPS) and BeiDou Navigation Satellite System(BDS) which can provide higher precision location system and basically satisfy user's demands for location-based services in outdoor scenarios [3]. However, satellite system signals can be easily blocked, attenuated or reflected, which make these outdoor location systems arise problems like insufficient accuracy, unstable signals, no realization of seamless docking from indoor to outdoor location [5].

Nowadays, there are a number of indoor location technologies available including Radio Frequency Identification (RFID), bluetooth, ZigBee, Wireless Local Area Networks(WLAN), Ultra-Wideband(UWB). Among them, ZigBee based on Received Signal Strength Indicator(RSSI) is one of mainstream technologies [6]. The location-based

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models based on WSNs can be further divided into signal propagation model location algorithms and fingerprint model location models. The ranging-based location algorithm obtains the relative positional relationship (such as distance and angle) between nodes by means of RSSI, time of arrival (TOA), time difference of arrival (TDOA) or angle of arrival (AOA) [7]–[11].

A WSN consists of a large number of inexpensive and miniature wireless sensor nodes deployed in the monitoring area. Through wireless communication, the nodes form a self-organizing network with the ability to collaboratively sense and process related information [2]. The nodes in a WSN generally fall into two categories: beacon nodes and unknown nodes. A beacon node refers to a node whose location coordinates are known. It is also called an anchor node to obtain its own precise location through manual arrangement or a self-contained location device, and the proportion in the wireless sensor network is small. In wireless sensor networks, the fewer nodes are required in the same control area, so the optimal configuration scheme is proposed from the perspective of network power consumption and system efficiency. Therefore, reducing the number of nodes and improving node coverage is one of the research priorities. In the optimal node structure configuration, improving the node location accuracy is very important for the practical application of the wireless sensor network. Optimized location technology is very important for location-based applications and also can improve the accuracy of location information.

In the past, several interesting approaches have been used to tackle the problem of WSN node localization. In [15], the traditional square node layout deployed four CC2530 ZigBee nodes in the four corners of the 8m $\times$ 8m laboratory ground, and it improved the location accuracy by 10% using the improved weight-based triangular centroid location algorithm. The location accuracy of the traditional layout scheme is low. In [16], the method mentioned that the RSSI within 5m as a non-sensitive area and 5m as a sensitive area and proposed an equilateral triangle location with a side length of 5m. The beacon node is located at the apex of the triangle. The node to be located is located in the triangle area. In the 15m $\times$ 10m area, the maximum location error is 22% through the combination of the three sides and the triangle centroid, which is 30% higher than the traditional location accuracy. The location accuracy of this method has been improved by modifying the node positioning scheme, but it can't meet the requirement of high precision. Wang [17] focused on the location of traditional equilateral triangles. It is pointed out that in the edge of the region where the equilateral triangle is positioned, the necessary anchor nodes for location are lacking, and the anchor nodes have similar influences on the boundary line of the triangle region. The result is constantly changing. In [17], Hui proposed a method of adding anchor nodes. In the 13m $\times$ 6m area, 7 nodes are arranged with equilateral triangles with side length of 4m, and 3 anchor nodes are added in the edge region lacking anchor nodes to realize regional location with full coverage. Experiments show that the location accuracy in some areas is much better than that of traditional equilateral triangles. The location accuracy of this method is greatly improved, but the number of nodes in the same area increases more and the utilization rate of nodes decreases.

Additionally, [18] studied the use of particle swarm optimization (PSO) algorithm to optimize the support vector machine penalty parameter C and RBF kernel width σ for the classification problem only, compared with the traditional grid search algorithm optimization support vector machine. This method has a better effect. In [19], Yin *et al.* employed Particle Swarm Optimization (PSO) for SVM parameter optimization, which significantly improved the location accuracy of the navigation system, but it only optimized the penalty parameter C and the loss function variable $\in$, and did not optimize the RBF kernel width σ. On the basis of changing the layout scheme of nodes, combined with the optimization of PSO algorithm, the location accuracy can be better improved.

In this paper, the relationship between the distance and the RSSI of the logarithmic loss model is firstly analyzed, and the corresponding relationship between different distance ranges and RSSI is obtained. Secondly, the influence of the retention of the fractional number of RSSI values on the location accuracy is analyzed. Then, according to the relationship between distance and RSSI, the algorithm of equal arc triangulation is proposed, which can effectively compensate for the lack of large uncovered area at the edge of traditional equilateral triangle layout. Finally, in the same experimental environment, the square layout, the equilateral triangle layout, the improved triangle layout and the equal arc triangulation layout proposed in this paper are compared respectively. The experiment shows that the equal arc triangulation layout model has greatly improved the location accuracy compared with the square layout, the traditional triangular layout model and the improved triangular layout model. The coverage of 88% can be achieved by using equal-arc trilateral layout with the same number of locating nodes in the same area. This method effectively improves the utilization rate of nodes.

The rest of the paper is organized as follows. Section 2 brings forward a few related works. Section 3 focuses on the relationship between RSSI change rate and distance. Section 4 employs particle swarm optimization method for node localization. Section 5 presents an equal-arc triangular location algorithm. Section 6 evaluates the performance of the proposed work and Section 7 concludes the paper.

II. BACKGROUND

RSSI is the known transmitting power, the received power is measured at the receiving node, the propagation loss is calculated, and the propagation loss is translated into distance using a theoretical or empirical signal propagation model. Thus, by measuring the strength of the received signal, the approximate distance of the transceiver node can be calculated. After obtaining the distance information between the anchor node and the unknown node, the location of the unknown node can be calculated by the trilateral

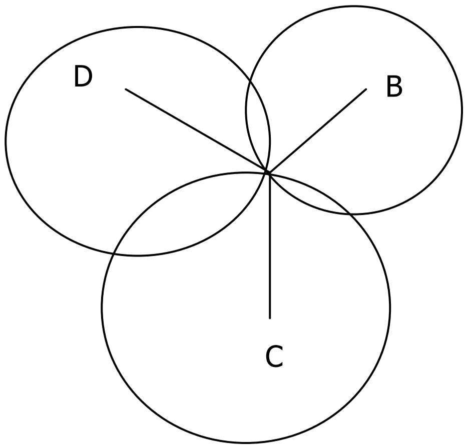

FIGURE 1. Three-side measurement.

method or the maximum likelihood estimation method. However, the above scheme is only a mathematical model of electromagnetic waves propagating in an ideal free space, and the situation in practical applications is much more complicated, especially in WSNs with a plenty of nodes. Problems such as reflection, multipath propagation, and antenna gain all have different propagation losses for the same distance.

The main advantages of RSSI are as follows:

- Easy to use. RSSI is the signal strength from the other party when the nodes communicate with each other. When the wireless sensor nodes can communicate normally, the value can be directly extracted from the hardware without other equipment. This is important for reducing network cost and complexity.
- Symmetry. RSSI values tend to be symmetrical, so measuring the RSSI value between two nodes can be done by sending and receiving a message packet without the need to return the message packet. It is significant for reducing the complexity of the location algorithm or the application scenario where the location accuracy is not very high.
- Distance is monotonic. The RSSI value has a monotonic relationship with the distance between nodes and becomes smaller as the distance increases. Therefore, RSSI can meet the requirements of both ranging and non-ranging algorithms.

During the sensor node localization process, the unknown node usually uses the trilateral method to calculate its location after obtaining the distance to the adjacent beacon node or obtaining the relative angle between the adjacent beacon node and the unknown node. Trilateral measurement technology is a coordinate calculation method used in GPS positioning systems. When the GPS transceiver is known to be away from four different satellites in the sky, the coordinates of these satellites are known (because the trajectory can be predicted), so the equivalent of finding the intersection point of 4 circles at this time is the location result. Consider the 2-dimension case, as shown in Fig.1.

At this point, it is assumed that the coordinates of B, C, and Dare (x_1, y_1), (x_2, y_2), (x_3, y_3), respectively, and their distances to the intersection point are r_1, r_2, r_3, respectively, and the coordinates of the intersection point (x, y), we can list the following three formulas (Equation 1):

$$\begin{aligned}(x-x_1)^2+(y-y_1)^2&=r_1^2\\(x-x_2)^2+(y-y_2)^2&=r_2^2\\(x-x_3)^2+(y-y_3)^2&=r_3^2\end{aligned}\tag{1}$$

In equation set (1), subtract the third formula from the first formula and the second formula to get the equation set (2).

$$\begin{aligned}(2x_1-2x_3)x+(2y-2y_3)y+x_3^2-x_1^2+y_3^2-y_1^2&=r_3^2-r_1^2\\(2x_2-2x_3)x+(2y_2-2y_3)y+x_3^2-x_2^2+y_3^2-y_2^2&=r_3^2-r_2^2\end{aligned}\tag{2}$$

The above formula can be converted into the form of AX = b

$$A=\begin{bmatrix}2x_1-2x_3 & 2y_1-2y_3\\2x_2-2x_3 & 2y_2-2y_3\end{bmatrix},\quad X=\begin{bmatrix}x\\y\end{bmatrix},$$
$$b=\begin{bmatrix}r_3^2-r_1^2+x_1^2-x_3^2+y_1^2-y_3^2\\r_3^2-r_2^2+x_2^2-x_3^2+y_2^2-y_3^2\end{bmatrix}$$

So the value of the calculated coordinates (x, y) is shown in Equation 3:

$$X=A^{-1}b=\begin{bmatrix}2x_1-2x_3 & 2y_1-2y_3\\2x_2-2x_3 & 2y_2-2y_3\end{bmatrix}^{-1}\times\begin{bmatrix}r_3^2-r_1^2+x_1^2-x_3^2+y_1^2-y_3^2\\r_3^2-r_2^2+x_2^3-x_3^2+y_2^3-y_3^2\end{bmatrix}\tag{3}$$

At this point, it is necessary to discuss that the A^{-1} must exist. The necessary and sufficient condition for the value existence in this example is that the three points B, C, and D are not collinear. For the 2-dimensional case, we can estimate the coordinates of the unknown node when we know the distance from an unknown node to a known point of 3 different lines. Similarly, we can extend this result to the 3-dimensional case.

Since RSSI is easily affected by multi-transition effects, in order to improve the location accuracy, it is necessary to design the sensor node layout according to the characteristics of RSSI and transmission distance and find a feasible node layout method with less RSSI interference.

If the RSSI and the transmission distance satisfy a strict linear relationship, high location accuracy can be achieved. As a way of expressing electromagnetic energy, RSSI mainly transmits electromagnetic signals of 2.4G frequency. Although the wavelength of the band signal is relatively long and the penetrating power is good, it is impossible to strictly satisfy the linear relationship in the complex indoor environment by the influence of pedestrians and furniture. It is especially important to study the propagation characteristics of electromagnetic waves in the 2.4G band indoors, and

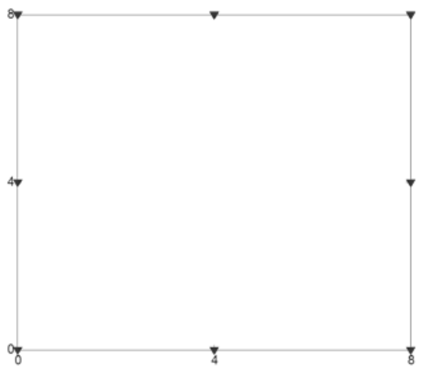

FIGURE 2. Quadrilateral layout.

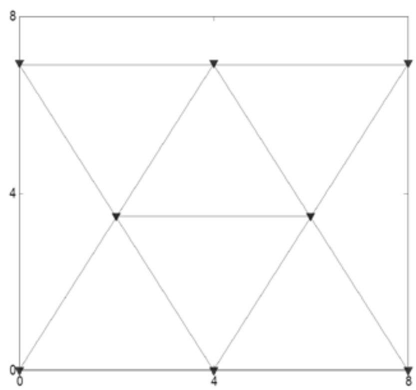

FIGURE 3. Trilateral layout.

to find a reasonable and efficient indoor sensor node layout, so as to reduce the RSSI interference.

At present, in the RSSI-based location, a common sensor node layout is quadrilateral layout, as shown in Fig.2. In order to reduce the influence of RSSI interference, an equilateral triangle layout based on the quadrilateral deployment of sensor nodes has been proposed as shown in Fig.3. (The location areas in Fig.2 and Fig.3 are both 8m × 8m, of which "red inverted triangle" is the reference anchor node.)

Although the equilateral triangle has some improvements in location accuracy compared with the quadrilateral, there are some outstanding shortcomings, such as low coverage of the effective location area, low single-point coverage (the ratio of the total area of the effective positioning area to the number of nodes), and complex spatial structure. The area (such as irregular areas) is difficult to be laid out. Finding a better layout method not only has a greater improvement in location accuracy, but also a reasonable layout in a relatively complex spatial structure and a higher single-point coverage is extremely meaningful.

Because the nodes of the wireless sensor network are affected by the surrounding environment and the receiving and transmitting capabilities of the nodes themselves, it has a great impact on the coverage of the node network and the actual location effect. It is necessary to analyze the actual working performance of the nodes.

PSO is adopted in node location optimization. PSO is an iterative-based optimization algorithm. The system is initialized to a set of random solutions that search for the optimal value by iteration. But it does not have the crossover and mutation of the genetic algorithm, but the particle searches in the set of solution to follow the optimal particle. The advantages of PSO are that it is simple and easy to implement and there are not many parameters to adjust. It has been widely used in functional optimization, neural network training, fuzzy system control and other applications of genetic algorithms.

In recent years, researchers have extended the PSO algorithm to the constrained optimization problem. The key is how to deal with the constraint, that is, the feasibility of the solution. If the constraint processing is not good, the result of the optimization tends to be unable to converge and the result is an empty set. Constraint optimization based on PSO algorithm is mainly divided into two categories:

- Penalty function method. The purpose of the penalty function is to transform the constrained optimization problem into an unconstrained optimization problem.
- Limit the search range of the particle swarm to the conditional constrained cluster, that is, optimize within the feasible solution range.

III. THE RELATIONSHIP BETWEEN RSSI AND DISTANCE

The data acquisition hardware of the wireless sensor network is a ZigBee module with TI's CC2530F256RHAR as the main control chip, and the working frequency band is 2.4 GHz. The RSSI correspondence data was established at a distance of 0.1 m in the laboratory, and 100 RSSI values were measured at each measurement position. After the Kalman filter processing, the RSSI value at 1m is − 45.65dB (the value is determined by the relationship between the best communication distance and RSSI sensitivity), based on the log fading propagation model, fitted by least squares method, n is 3.

A. THE RELATIONSHIP BETWEEN RSSI CHANGE RATE AND DISTANCE

Free space is an ideal environment and signal propagation is not affected by other disturbances. In free space, the received signal strength is inversely proportional to the propagation distance. The formula for the free space propagation model is given below:

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \tag{4}$$

In the formula, $P_r(d)$ is the received signal strength, P_t is the transmitted signal strength, G_t is the transmit antenna gain, G_r is the receive antenna gain, λ is the signal wave length, d is the distance between the transmitter and the receiver, L is the system loss factor.

In practical applications, the free-space propagation model is no longer applicable due to diffraction, multi-effects and obstacles. Therefore, the logarithmic loss propagation model

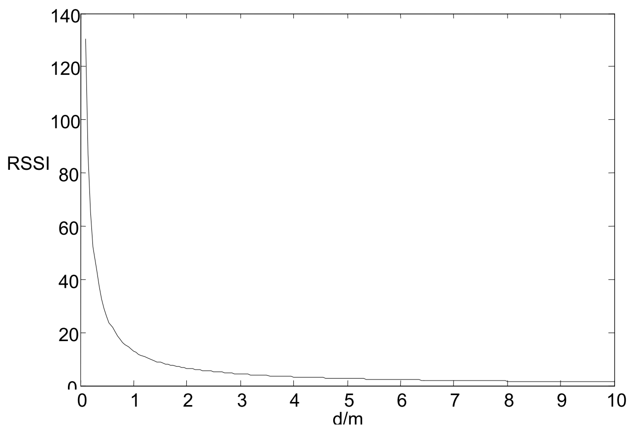

FIGURE 4. Relationship map between $|RSSI_i'|$ and distance.

is more suitable, and its formula is as follows:

$$P_r(d) = P_r(d_0) + 10n\lg\left(\frac{d}{d_0}\right) + X \tag{5}$$

d_0 is the near-ground reference distance, P_r (d_0) is the path loss value of the near-ground reference distance, d is the actual distance, P_r (d) is the exact path loss of the actual distance, and **n** is the path loss factor, which varies with the environment. *X* is random noise.

Usually the reference value d_0 is 1m, P_r (d_0) is available by measurement and is recorded as A. In order to make the calculated n a positive value, the first "+" on the right side of the medium number of (5) is changed to "−", then the relationship between the distance d_i at different positions and the received signal strength $RSSI_i$ is obtained as follows:

$$RSSI_i = A - 10n\lg(d_i) + X_i \tag{6}$$

In formula (6), A is the RSSI value at 1m, the unit is dB, n is the path loss factor, X_i is the random noise, i = 1, 2, 3, … are the tag values of different positions. Seeking the deviation on both sides of (6):

$$|RSSI_i'| = \left|\frac{-10n}{\ln 10}\cdot\frac{1}{d_i}\right| = |-4.35n|\cdot\frac{1}{d_i} \tag{7}$$

The fitting parameter n = 3, the value range is from 0.1m to 10m, the interval is 0.1m, i = 1,2,3,… are the marker values of different positions, and the distance relationship between $\left|RSSI_i'\right|$ and d_i is obtained, as shown in Fig.4.

Formula (6) is transformed into the independent variable $RSSI_i$, and the dependent variable d_i is showed in the formula (8), as follows:

$$d_i = 10^{\frac{A-RSSI_i+X_i}{10n}} \tag{8}$$

In formula (8), X_i is ignored, and A is the measured value, which is − 45.65 dB, n is 3. Then we have formula (9) as follows:

$$d_i = 10^{\frac{-45.65-RSSI_i}{10*3}} = 10^{\frac{-45.65-RSSI_i}{30}} \tag{9}$$

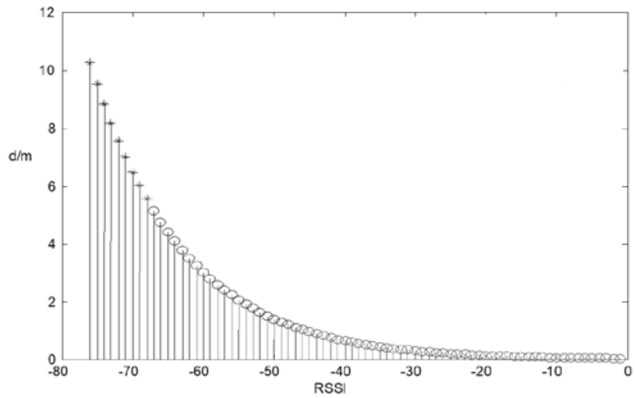

FIGURE 5. Relationship map of RSSI value and distance.

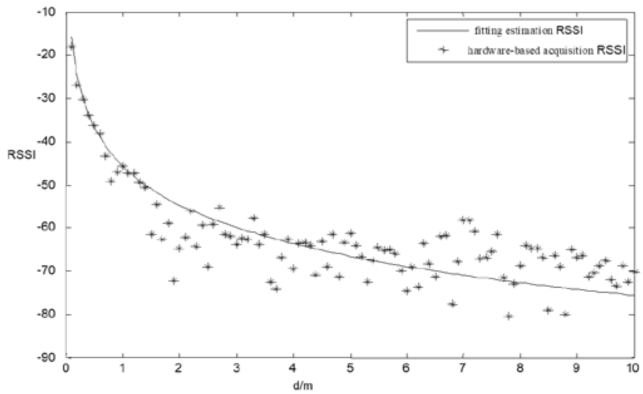

FIGURE 6. Relationship map of the hardware-based $RSSI_i$, the fitting estimation $\hat{RSSI}_i$ and distance d_i.

Using formula (9), Fig.5 is obtained. The RSSI value ranges from − 76.00 dB to − 1.00 dB, and the distance ranges from 0 m to 10 m with an interval of 0.1 m.

In formula (6), X_i is negligible, A is measured at 1m, and its value is − 45.65dB, i = 1, 2, 3,… are the marker values at different positions, and the value n is 3. Then we have formula (10) as follows:

$$RSSI_i = -45.65 - 10*3\lg(d_i) = -45.65 - 30\lg(d_i) \tag{10}$$

Using formula (10) at intervals of 0.1 m, the fitting estimates are calculated for different distances in the range of 10 m, and i = 1, 2, 3, … are the marker values at different positions. The relationship between the hardware-based acquisition $RSSI_i$ by Kalman filter and the fitting estimation $\hat{RSSI}_i$ and distance d_i is shown in Fig.6.

It can be observed from Fig.5 that as the distance increases, the changing rate of change of RSSI gradually decreases, that is, the RSSI value decreases with the increase of the distance per unit distance (1 m). In Fig.5, in the range of 1m to 10m, as the distance increases, the RSSI mapping value per meter decreases, and if the collected RSSI is disturbed, the distance error also increases. It is known from Fig. 6 that as the distance d_i increases, $RSSI_i$ has the larger wobbling

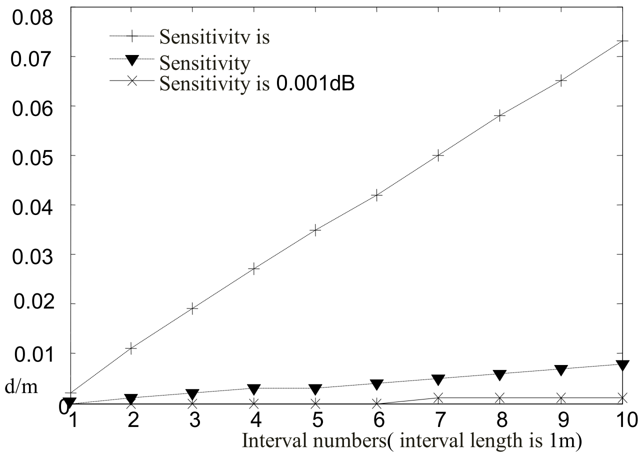

FIGURE 7. RSSI sensitivity.

amplitude around $\hat{RSSI}_i$, the fitting degree becomes worse and worse, and the disturbance becomes larger and larger. In the ranging location based on the log fading model, the farther the distance is, the less the RSSI mapping value is, the lower the fault tolerance rate is, the larger the RSSI disturbance is, and the larger the location error caused by the disturbance is. According to the experimental results and actual use requirements, the communication distance is chosen to be 4m.

B. RSSI SENSITIVITY ANALYSIS

RSSI-based localization technology calculates the location information of unknown nodes according to the signal energy received by nodes, so it is an important problem to analyze the sensitivity characteristics of nodes in node localization. Although the sensitivity of the RSSI data collected by the hardware is 1 dB, in the process of data processing, there will always be a decimal case. The relationship between RSSI with different sensitivity changes and distance is shown in Fig.7.

In Fig.7, when the RSSI sensitivity is 0.1dB, the RSSI of each interval range (interval length is 1m) changes by 0.1dB, and the mean value of the corresponding distance changes from 0.002m to 0.073m. When the RSSI sensitivity is 0.01dB, each interval range changes by 0.01 dB, and the mean value of the corresponding distance change also increases gently from 0 m to 0.008 m. When the RSSI sensitivity is 0.001 dB, the RSSI changes by 0.001 dB in 0 m to 6 m, and the distance does not change. The RSSI changes by 0.001 dB and the distance changes by 0.001 m in 6 m to 10 m. In actual location, the appropriate number of decimal places should be reserved according to the different communication distances selected. Since the optimal communication distance used in this paper is 4m, the fractional bits of the RSSI value retain two decimal places.

IV. PSO OPTIMIZED NODE LOCALIZATION

Suppose that in a D-dimensional target space, there are N particles representing potential problem solutions to form a group, where the i-th particle is represented as a D-dimensional vector, $X_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]^T$ i = 1, 2,...,N; the position of the i-th particle in the D-dimensional search space is X_i, the flight speed is $V_i = [v_{i1}, v_{i2}, \ldots, v_{iD}]^T$; recorded P_i as the optimal position of the individual searched for the i-th particle so far, $P_i = [p_{i1}, p_{i2}, \ldots, p_{iD}]^T$ Recorded P_g as the global optimal position that the particle swarm has searched so far, $P_g = [p_{g1}, p_{g2}, \ldots, p_{gD}]^T$, the particle updates the speed and position according to equations (11) and (12) in each iteration:

$$V_i^{t+1} = wV_i^t + c_1 r_1 (P_i^t - X_i^t) + c_2 r_2 (P_g^t - X_i^t) \quad (11)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (12)$$

In formulas (11) and (12), i = 1, 2, 3, ..., N; "t" is the number of iterations; "w" is the weighting factor, which is between 0.1 and 0.9; c_1, c_2 is the learning factor, respectively adjusting the maximum step size of the direction flight between the best individual particles and the best global particles, if appropriate, c_1, c_2 can speed up convergence and is not easy to fall into local optimum, usually make $c_1 = c_2 = 2$; r_1, r_2 is a random number between [0,1]. The particles continue to learn and update, and finally find P_g the global optimal solution. The particle swarm algorithm in this paper is as follows:

Step 1: Initialize the total number of particles, particle dimensions, particle coordinate positions, learning factors, speed limit, local best values and global best values.

Step 2: Calculate the particle fitness value and update the local and global best values according to the fitness value.

$$d_i = \sqrt{(x_D - x_i)^2 + (y_D - y_i)}\ (i = 1, 2, 3) \quad (13)$$

$$FitValue = \sum_{i=1}^{3} (d_i - d_i')^2\ (i = 1, 2, 3) \quad (14)$$

In the above formula, (x_D, y_D) is the particle coordinate, (x_i, y_i) is the beacon node coordinate, d_i is the distance between the particle and the beacon node, d_i' is the distance calculated from the measured RSSI value of the beacon node.

Step 3: Determine whether the current iteration number reaches the upper limit or whether the optimal solution accuracy meets the requirements. If the condition is met, the program ends; otherwise, the next step is performed.

Step 4: Update the particle position and speed and jump to step 2.

The algorithm uses the particle swarm optimization algorithm to optimize the location. The initial particle number is 40, the particle dimension is 2, the learning factor $c_1 = c_2 = 2$, the speed limit is 8, the weighting factor w = 0.729, and the number of iterations is 100.

V. AN EQUAL-ARC TRIANGULAR LOCATION METHOD

Nowadays, according to the indoor location technology of ranging, layout model of beacon node generally has a square layout model, a traditional triangular layout model and an improved triangular layout model. In order to boost the indoor location precision, control the cost of beacon nodes efficiently and optimize node resources, the paper proposes an equal-arc triangular location layout model.

A. FILTER PROCESSING

The RSSI value has a large fluctuation in the measurement process, and the filtering can effectively remove the disturbance. The Kalman filter is used to process the RSSI value. The original state equation and measurement equation of the Kalman filter are as follows:

$$x_k = A_K x_{k-1} + B_k u_{k-1} + w_{k-1} \tag{15}$$
$$y_k = C_k x_k + v_k \tag{16}$$

In the formula, u_k is the state control input variable. When the system control input does not exist, it is 0. A_k is $n \times n$ the gain matrix of the state variable, B_k is the $n \times l$ control matrix, c_k is the $m \times n$ observation matrix, m is the y_k dimension, and n is the x_k dimension. The specific process is as follows:

Step 1: The current RSSI value is predicted based on the state equation. $\hat{x}_{k-1}$ is the state optimum value at time k − 1, and $\hat{x}'$ is the state estimation value at time k.

$$\hat{x}'_k = \hat{x}_{k-1} \tag{17}$$

Step 2: Estimate the variables at the current moment. p_{k-1} is the value of the variable at time k-1, p'_k is the value of the prior variable at time k.

$$p'_k = p_{k-1} \tag{18}$$

Step 3: The Kalman gain at time k is obtained from the prior estimate of the k-time variable. p'_k is the observed noise of each set of RSSI values, H_k is the Kalman gain, R_k is the observation error, and R_Avg is the mean value of the measured RSSI.

$$H_k = p'_k (p'_k + R_k)^{-1} \tag{19}$$
$$R_k = ((RSSI_1 - R\_Avg)^2 + \cdots + (RSSI_n - R\_Avg)^2)/n \tag{20}$$

Step 4: The predicted value is updated based on the current observation the Kalman gain H_k of the previous step. y_k is the RSSI observation of time K.

$$\hat{x}_k = \hat{x}'_k + H_k(y_k - \hat{x}'_k) \tag{21}$$

Step 5: The predicted variable value is updated according to the K time

$$p_k = (1 - H_K) P'_K \tag{22}$$

The iterative termination condition is that the absolute difference between two adjacent moments of the variable is less than 0.001, ie. $|p_k - p_{k-1}| < 0.001$. The Kalman gain at this time is the stable gain of the Kalman filter. Combining the obtained stable gain, the optimal RSSI value at each moment can be obtained. The initial estimate of RSSI is 0, and the initial estimate of the variable is 10, that is $x_0 = 0$, $p_0 = 10$.

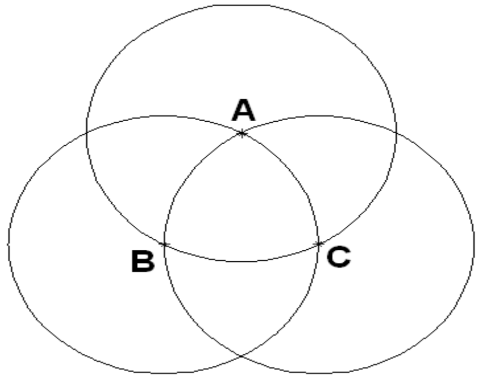

FIGURE 8. Node deployment diagram of equal arc triangulation.

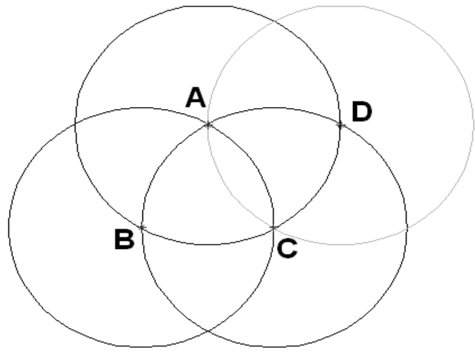

FIGURE 9. Multi-node deployment diagram of equal arc triangulation.

B. AN EQUAL-ARC TRILATERAL MODEL

Combined with the relationship between RSSI and distance in the second section, different optimal communication distances are adopted according to different requirements, and the node to be tested is always in the optimal communication range, and the optimal communication distance of the node is maximized. As shown in Fig.8, the "∗" represents the sensor node, the circle represents the optimal communication range of the beacon node, and the radius is r, and each node is on the boundary of the optimal communication range of other nodes. After the node is deployed, each adjacent three nodes can always form an equi-arc triangulation area surrounded by the arcs of AB, BC and CA in Fig.8, each arc length being 1/6 circumference long. The points in this area are all within the optimal communication range of the three sensor nodes. As a result, the three points A, B and C are the optimal anchor nodes in the current region, and the anchor nodes in the environment of a large number of deployed anchor nodes need only be combined with anchor nodes like A, B and C, which can determine its location.

As can be seen from Fig.9, in the area surrounded by the equal-arc triangular ABC, a part of the area is also in the area surrounded by the equal-arc triangular ACD. The points to be measured in the overlapping area can be selected in the ABC or ACD combination to prevent anomalies due to special reasons, and thus the selectivity plays an auxiliary role in improving the location accuracy.

C. THE EQUAL-ARC TRIANGULAR LAYOUT CONTROL RSSI OUTLIERS

In the triangular location layout proposed by Jian et al. [16], if the collected RSSI value exceeds the optimal communication distance "r", it will repeat taking the value continuously. In the actual measurement, the collected RSSI value will maintain the abnormality for a period of time in a short period of time for some reasons. If continues to keep in accordance with the method of Jian et al. [16], the acquisition delay will be greatly increased. In this paper, based on the selected communication distance r, the logarithmic attenuation model is used to calculate the three optimal RSSI values selected by the base station. If the obtained distance is greater than the communication distance "r", the current value is determined to be an abnormal value, and the base station reselects three optimal RSSI values for calculation, and the maximum number of acquisitions is three times. If there is still a value exceeding the distance "r" after three acquisitions, the location system re-assigns the current outlier to r, where r is 4 m.

D. THE EQUAL-ARC TRIANGULAR LOCATION ALGORITHM

The Equal-Arc Triangular Location algorithm steps are as follows:

Step 1: Initialize the beacon node network model

Step 2: Unknown nodes periodically send their own information

Step 3: After receiving the information, each beacon node records the RSSI measurement value of the same unknown node and records its value into the corresponding RSSI array.

Step 4: Each beacon node uses Kalman filter to process RSSI values

Step 5: Each node transmits the RSSI value obtained in step 4 to the base station, and the base station sorts the RSSI values of each node, takes the maximum three values, and converts them into distances, which are respectively d_1, d_2, d_3.

Step 6: Determine whether d_1, d_2, d_3 are greater than r. If it is greater than r, then re-take the value. If accumulate 3 times and it is still greater than r, then set $r = 4$m; otherwise, calculate according to the original value. It is worth noting that the square layout model does not have this step.

Step 7: Using the particle swarm optimization location algorithm, iterate 10 rounds, search 100 times per round, and calculate the position (x, y) of the point to be measured.

VI. EXPERIMENTAL ANALYSIS

A. EXPERIM ENTAL SETTINGS

In the 8m × 8m area of the laboratory, carry on node localization experiment of WSNs. The optimal communication distance is 4m, collecting 100 RSSI values at each measurement position, and then performing Kalman filtering on the data, where the algorithm iterative termination condition is that the absolute difference between two adjacent moments of the variable is less than 0.001, and the initial estimated value of the variable is 10, the initial estimation value of RSSI is 0,

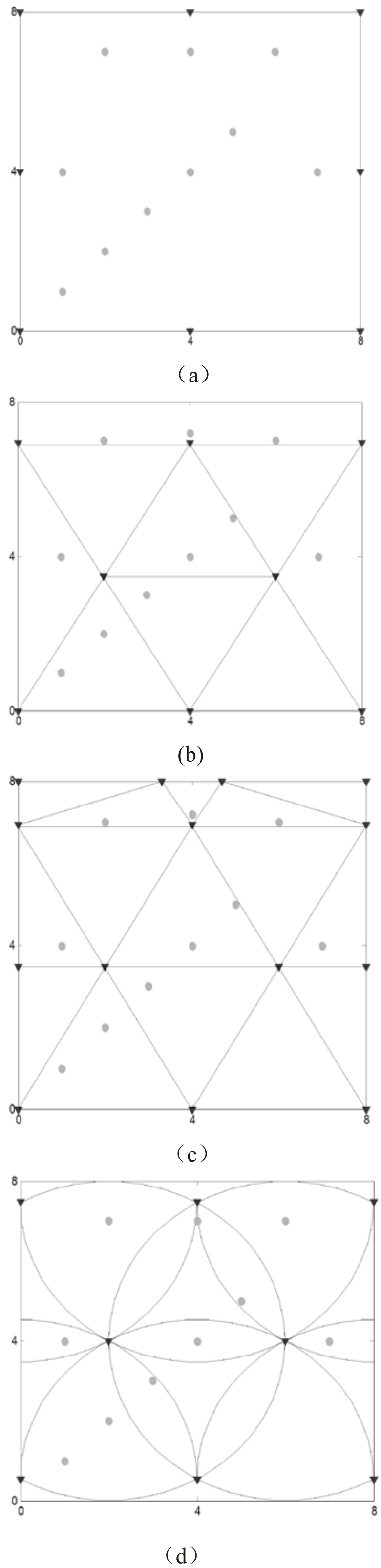

FIGURE 10. **Four node location layout distribution maps.**

and the RSSI value at 1 m is −45.65 dB. Based on the log fading propagation model, the n fitted by the least squares method is 3. Particle swarm optimizes algorithm for location optimization, the initial particle number is 40, the particle dimension is 2, the learning factor $c_1 = c_2 = 2$, the speed limit is 8, the weighting factor $w = 0.729$, and the number of iterations is 100.

The improved triangular layout model and the equi-arc triangulation layout model deploy beacon nodes, as shown in (a), (b), (c), and (d) of Fig.10. The inverted triangle represents the beacon node, and the dot represents the node to be tested. The coordinates of the 10 nodes to be tested are (1,1), (2,2), (3,3), (4,4), (5,5), (4,7), (1,4), (7,4), (2,7), (6,7). Choose the best communication distance of 4m.

B. RESULTS ANALYSIS

By comparing the four layout types shown in (a), (b), (c), and (d) of Fig.10, it is easy to know that the square layout in (a) does not involve any refinement of the regional model; in (b) the traditional triangular layout area coverage is 65%, that is, 42 m^2; (c) the improved triangular layout can fully cover, but adds 6 nodes; (d) The medium arc triangular layout area coverage is 88%, that is, 56 m^2. Compared to the layout models in (b) and (c), the area of the equal-arc triangle has a higher area coverage percentage per unit node.

After processing the data of the four location layouts, the error comparison of the four location layouts is obtained, as shown in Fig.11. By observing Fig.11, we can draw the following conclusions:

- Among the four location layouts of square layout, traditional triangular layout, improved triangular layout and equal arc triangular, the equal arc triangular has the best location accuracy, the traditional triangle and the improved triangle layout are the second, and the square layout performed worst in Location accuracy.
- In the test of the first five points, the improved triangle layout and the traditional triangle layout have little difference in Location accuracy. In the last five points, the improved triangle layout is improved compared with the traditional triangular layout. The main reason is that several nodes are added. Compared with the 10 points to be tested in the two layouts, the improved triangle layout is 12% higher than the traditional triangle layout.

It can be seen from Table 1 that the average errors of the four layouts of square, conventional triangle, modified triangle and equal arc triangular are 4.298m, 1.782m, 1.572m and 0.816m respectively. The equal arc triangular layout has an average location accuracy of 81%, 54%, and 48% respectively, compared to the square layout, the traditional triangular layout, and the improved triangular layout. The maximum and minimum errors of the four location layouts are shown in Table 1.

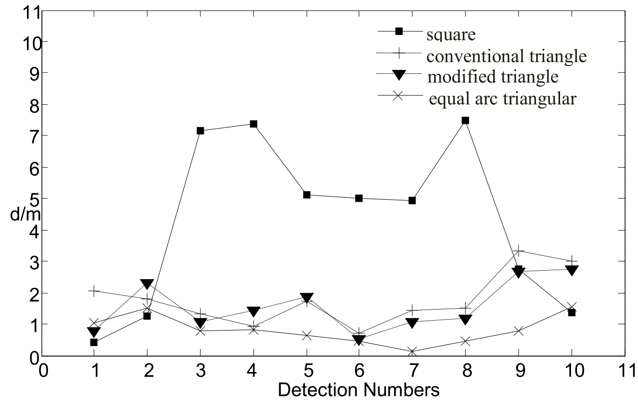

FIGURE 11. Performance of the four node location layouts.

TABLE 1. Comparison of maximum, minimum and average error in four deployments.

Deployment / Error	Max Error(m)	Min Error(m)	Ave Error(m)
square deployment	7.473	0.419	4.289
conventional triangle deployment	3.330	0.710	1.782
modified triangle deployment	2.732	0.541	1.572
equal arc triangular deployment	1.563	0.113	0.816

VII. CONCLUSION

By analyzing the relationship between RSSI and distance, the RSSI becomes more and more unstable with the increase of distance. The distance fault tolerance based on logarithmic fading model is getting lower and lower, and the ranging error is getting larger and larger. In order to utilize the signal with higher ranging accuracy, an equal arc triangulation location algorithm is proposed. Compared with the traditional square layout, the traditional triangular layout and the improved triangular layout, the algorithm has improved location accuracy by 81%, 54% and 48% respectively. In the experiment, the traditional triangular layout area coverage was 65%, while the equal arc triangular coverage was 88%, an increase of 23%. The equal-arc triangulation location algorithm proposed in this paper can not only improve the location accuracy, but also control the sensor costs reasonably. The equal-arc triangulation algorithm is simple to operate, has no additional hardware for expansion and is suitable for wide-ranging promotion. This paper carries out experimental analysis under relatively ideal environment. In the case of large environmental disturbance, it needs to adopt efficient corresponding methods to solve the problem. Node layout research based on two-dimensional level has limited application scope. Gradually realizing efficient location in three-dimensional level will play a greater role in intelligent buildings, large shopping malls and other scenarios.

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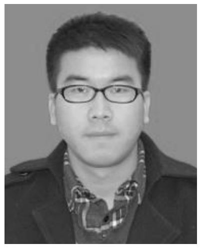

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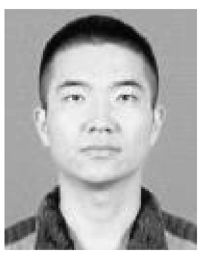

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