Indoor Location based on Particle Swarm Optimization and BP Neural Network

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Abstract

The ideal positioning methods are of great importance in pervasive computing services. RFID technology with low cost and simple structure is often used for indoor positioning. Based on the advantages of RFID technology, an indoor positioning method based on particle swarm to optimize BP neural network and reader deployment is proposed. Since prediction results of traditional BP neural network are easy to fall into local optimum, this method uses PSO to optimize the weights and thresholds of BP neural networks to avoid the shortcomings. The particle swarm optimization is used to optimize the reader's position, so that the Euclidean distance between the reference tags is appropriate and the tolerance of the positioning system to signal fluctuations can be improved. In addition, in order to improve the positioning accuracy, the experimental data are processed by Gauss filtering method. The experimental results show that the proposed method has better performance than traditional methods.

Keywords

Radio frequency identification; particle swarm optimization algorithm; BP neural network; reader deployment; indoor position.

1. Introduction

With the rapid development of wireless sensor, indoor positioning information service has become a hot topic. Global Positioning System（GPS） is difficult to meet the requirement of precision positioning under the indoor environment because it lacks of line of sight between the satellite receiver and satellite transmission [1]. In recent years, researchers have put forward a variety of positioning technology, such as infrared, ultrasonic, radio frequency identification (RFID), UWB, WIFI, Bluetooth and ZigBee. Among them, the RFID technology is suitable because its price is very low and its data transmission is based on radio-wave communications. The concept of RFID, which is recently used in numerous industrial applications from asset tracking to supply chain management [2–6], has received significant attention among the researchers [7]. The traditional RFID positioning method can be mainly divided into two sorts: geometric methods and the algorithms based on RSSI [8].

A series of researches related to geometric methods have been conducted recently. Shen et al. used TOA measurements in indoor environments to estimate the location of passive object [9]. The TOA method can achieve high accuracy of ranging in the line-of-sight and multipath environment, but it needs accuracy of high clock synchronization which is expensive between the transmitting end and receiving end. Jung et al. employed TDOA localization algorithm in and evaluated the performance of the proposed localization method [10]. Wen and Liang proposed an indoor AOA estimation algorithm, the auto-focusing method is first used to obtain a coherently combined matrix among different subcarrier frequencies and then the study implement Toeplitz processing in the coherently combined matrix to present the received multipath signs in spatial domain. The proposed method outperforms the conventional auto-focusing method with low error bias, even though all multipath signals are highly correlated [11].

The geometric method is to obtain the distance between the tag and the reader based on the relationship between signal strength loss and distance in the propagation model [12]. But indoor signal transmission is unstable, the results based the signal propagation model are lack of applicability in the indoor environment. At present, the BP neural network is usually used in indoor positioning. The method is sensitive to initial weight and threshold sensitivity, easy to fall into local optimal and slow convergence speed. In addition, the existing method does not consider the deployment of RFID reader when the algorithm is improved. Therefore, we propose to optimize the parameters and reader deployment of BP neural network algorithm with particle swarm algorithm to improve the positioning effect. The experimental results show that the positioning accuracy and stability of BP neural network algorithm are better than original positioning.

The remaining part of this paper is organized as follows: In Section 2 we state our approach and present our algorithm. In Section 3 we optimize the position of reader. Section 4 demonstrates the hardware experimental method and the results. Finally, the concluding remarks are made in Section 5.

2. Indoor Positioning System

2.1 RFID system

RFID indoor positioning systems include readers, reference tags, antennas and servers [13], as shown in Fig.1. The RFID reader is responsible for powering and communicating with a tag. RFID tags are widely applied in many industries, for example, an RFID tag attached to an automobile during production can be utilized to monitored its progress in the assembling, RFID-tagged containers can be tracked during the transportation [14,15]. Unlike active RFID tags that are powered by batteries, passive RFID systems however communicate through the backscatter radio links due to that passive tags (no batteries powered) can only passively collect energy from the in-air backscattered radio signal. So we select passive RFID tag in our experiment. The RFID antenna captures energy and transfers the tag's ID (the tag's chip coordinates this process). The RFID middleware can process the received data and calculate the location information.

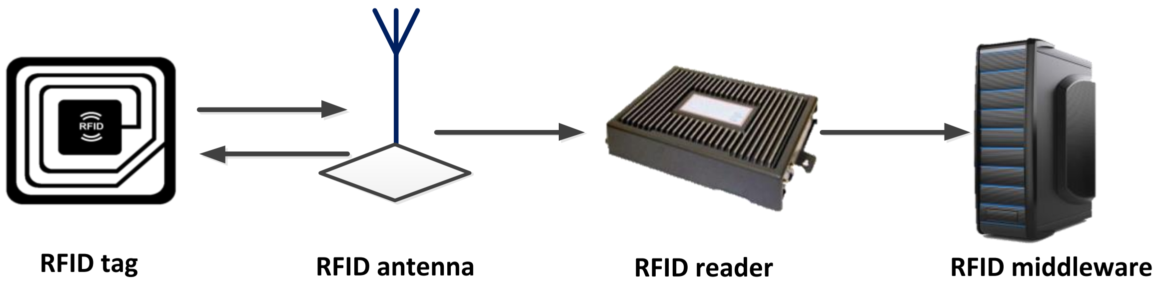

Fig. 1 RFID positioning system.

2.2 RSSI variation due to multipath shadowing

The frequency of RFID is generally in the range of 125kHz to 5.8GHz. This paper uses passive RFID Ultra High Frequency (UHF) tags which don't require the battery to provide energy and reach about 20 meters of communication range in the open condition. The tags should be activated by the interrogation and reply by sending a unique identification string back at the reader [16]. Then the reader will receive the data of the tag feedback, including time, RSSI value and ID information.

The signal strength of the reference tag is not a stable value. The signal strength of the same reference tag will be affected by a lot of indoor interference factors, and the fluctuations cannot be ignored, because the fingerprint must truly reflect the signal strength characteristics and can guarantee the user's location estimation accuracy in the online phase [17]. RSSI of the reader for acquiring the positioning tag decreases with the increase of the propagation distance, and the relationship between the RSSI value and the propagation distance is shown in Eq. (1).

$$RSSI(d) = (\frac{\lambda}{4\pi d})\left|1+\sum_{m=1}^{M}\Gamma_m \frac{d}{d_m} e^{-j(d_m-d)}\right|^2 \tag{1}$$

Where d is the distance between the reader and tag, λ is the path coefficient, M is the total number of reflections, Γ_m is the coefficient of the m th, and d_m is the length of the m th reflection path.

In the actual scene, the indoor obstacle will affect the positioning result, which leads to the phenomena of signal reflection, diffraction and scattering. The common signal path loss model in indoor environment is the logarithmic model represented by Eq. (2).

$$PL(d) = PL(d_0) + 10\phi \log_{10} \frac{d}{d_0} + X_\delta \tag{2}$$

Where $PL(d_0)$ is path loss for reference distance d_0, ϕ is path loss exponent and X_δ denotes a Gaussian random noise with zero mean and standard deviation of δ.

For a given physical environment, the predicted loss path model can be analyzed from the measured data. As shown in Fig.2, there is some discrepancy between the actually measured value of RSSI and the value obtained from the loss path model.

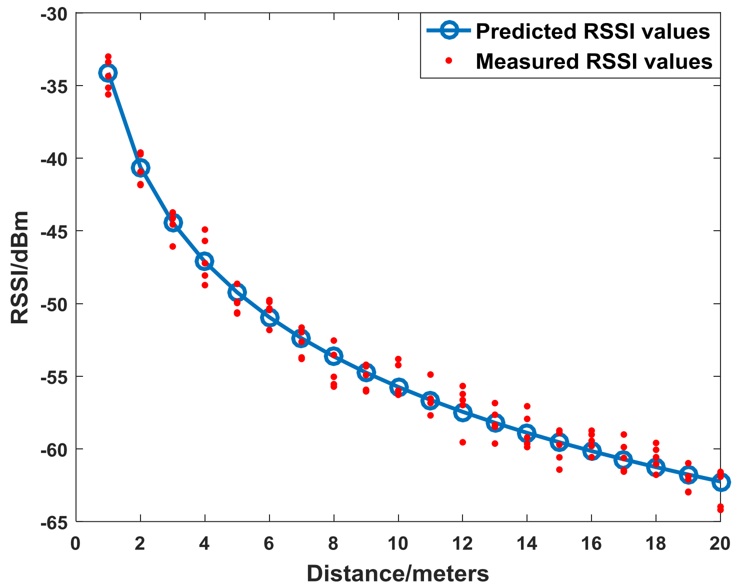

Fig.2 Relation between RSSI and distance.

2.3 BP neural network optimized by Particle Swarm Optimization algorithm

In order to improve the performance of BP neural network, we use Particle Swarm Optimization algorithm (PSO) to find the weights and thresholds of the BP neural network. PSO is a typical representative of swarm intelligent algorithm to search for the best solution by simulating the movement of flocking of birds. Each particle in the PSO algorithm represents the weight and threshold of the BP network, and each particle corresponds to a fitness value determined by the fitness function. [18]The sum of the absolute value of the prediction error of training data is taken as the individual fitness value. The smaller the individual fitness value is, the better the individual is. The PSO algorithm obtains the optimal weights and thresholds of the network by finding the minimum fitness value, where the fitness function is shown in Eq. (3) [19].

$$Fit = \frac{1}{N}\sum_{p=1}^{N}\sum_{q=1}^{M}(O_{p,q} - o_{p,q})^2 \tag{3}$$

Where Fit is the particle fitness function; N is the number of training samples, M is the number of output nodes of the neural network, $O_{p,q}$ is the expected output value of the q th node of the p th sample, $o_{p,q}$ is the actual output of the q th node of the p th sample value.

Particles keep updating speed and position while looking for space until the fitness function value reaches the set fitness value. Particle velocity and position are continuously updated according to Eq. (4) and Eq. (5).

$$v_{id}(t+1)=uv_{id}(t)+c_1rand_1(p_{id}-x_{id}(t)+c_2rand_2(p_{gd}-x_{id}(t)) \tag{4}$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \tag{5}$$

Where u estimate the inertia of the particle parameters; $c1$ and $c2$ denote cognitive coefficient and social coefficient, $rand1$ and $rand2$ are random values between 0 and 1. v_{id} is the velocity of the particle at the t th; x_{id} is the position of the particle at the t th; p_{id} is best location for all the particles; p_{gd} is the best location. Positioning process is divisible into offline phase and online phase. In the offline phase, we establish the positioning model of indoor position.

In the online phase, we collect RSSI values after Gaussian filtering to obtain the GRSSI vector. The GRSSI vector is taken as the input of the positioning model and (x,y) obtained by the positioning algorithm is the estimated position of the tag.

3. PSO algorithm for readers deployment

Reader deployment is usually based on experience which does not get best performance of position. In order to improve the accuracy of position, we use PSO to optimize the reader deployment.

3.1 Deploy readers

When the number of readers is determined, readers are deployed according to the principle that signal space Euclidean distance should be as big as possible while variance of signal space Euclidean distance as small as possible. The value of RSSI measured at same point during positioning fluctuates of Gaussian distribution constantly. Therefore, the positioning result is related to the Euclidean distance of the signal space between reference tags. The Euclidean distance of a reference tag refers to the average Euclidean distance of all reference labels within 2 meters of the reference point, where the Euclidean distance of the signal space is defined as follows:

If $RSSI_s=(RSSI_s^1,RSSI_s^2,\cdots,RSSI_s^P)$ and $RSSI_t=(RSSI_t^1,RSSI_t^2,\cdots,RSSI_t^P)$ are the Pth reader received the RSSI vector of the Sth and the Tth reference tags respectively, the Euclidean distance of the signal spaces between the Sth and the Tth reference tags is given by Eq. (6)

$$D_{S,T}=\sqrt{\sum_{k=1}^{P}(RSSI_S^k-RSSI_T^k)^2} \tag{6}$$

Due to the real-time variation of positioning environment, the signal received at a certain location is a variable value rather than a definite value. Suppose a signal received by a reference tag is a random variable, which changes in a circle centered at a point O and in a radius r, as shown in Fig.3.

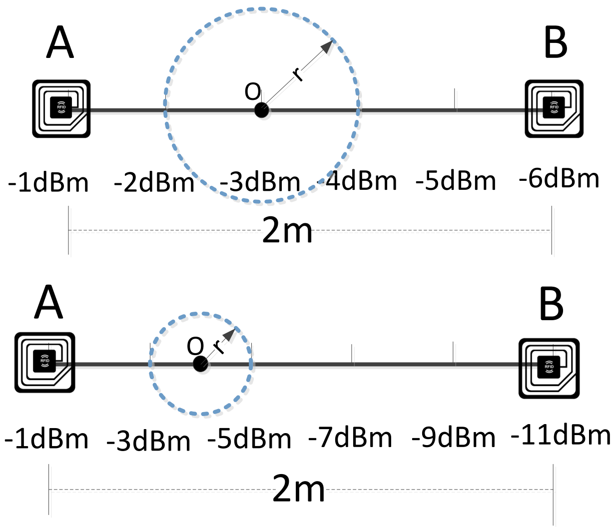

Fig.3 The influence of signal Euclidean distance on positioning accuracy.

As shown in Fig. 4, when the physical distances between reference labels A and B are both 2 meters, the larger the European distance is, the smaller the positioning error is. Therefore, the tolerance of the positioning system to signal fluctuations becomes stronger. In order to achieve the above goal, the optimization of reader deployment needs to make the difference between the average Euclidean distance of all reference tags and its standard deviation be the maximum, and the difference between two tags is calculated as shown in Eq. (7).

$$\max H = h - sqrt(\sum_{S=1}^{L}((\frac{\sum_{T\in F} D_{S,T}}{length(F)}) - h)^2) \tag{7}$$

Where H is the signal space Euclidean distance variance of all the reference tags in the target areas, h is the signal space Euclidean distance average of all reference tags, F is a point set in which the points are less than d meters from the i th reference tag, D is k-dimensional signal space Euclidean distance between the i th reference tags and j th reference tags, L is the number of all reference tags .

3.2 Reader Deployment Optimization

The essence of reader deployment is to make use of the size of the European distance of the signal space between reference tags to determine whether the signal coverage characteristics are favorable to the positioning needs of the system. In order to obtain the optimal solution of reader deployment, we use particle swarm optimization algorithm to get the optimal solution of reader deployment.

In order to PSO algorithm is used to optimize the deployment of the reader, each particle in the PSO algorithm represents the position of the reader, and each group of particles corresponds to a fitness value determined by the fitness function. The difference between the mean Euclidean distance of all reference tags and its standard deviation is taken as the fitness value of an individual, and the better the individual fitness value is, the better the individual is. The PSO algorithm obtains the optimal position of the reader by finding the maximum fitness value, which is used as the particle swarm fitness value in Eq. (7).

Particles keep updating speed and position while looking for space until the fitness function value reaches the set fitness value. Particle velocity and position are continuously updated according to Eq. (4) and Eq. (5).

4. Simulation results and analysis

In order to verify the feasibility of PSO to the deploy readers is optimized and test the stability of optimizing BP neural network algorithm optimized by PSO, we simulate experiments by MATLAB 2016a. The following Fig.4 shows the area of 16m * 16m with 256 reference labels and four readers (the distance of adjacent reference tag is 1meters).

Fig.4 Initial deployment of the reader.

4.1 Simulation scene

The wireless signal propagation empirical formula is used to simulate the RSSI value between the reference tag and the reader. In Eq. (8), $RSSI(d)$ denotes the signal strength of the reference tag when it is from the reader d meter and E indicates the transmitted energy. In the experiment, the desired parameters are set as the E 0dBm, $PL(d_0)$ 34.125dBm and ϕ 9.387 and we add Gaussian noise with zero mean and standard deviation of 3 used to simulate the actual environment due to signal reflection of walking and other factors on the RSSI value.

$$RSSI(d) = E - PL(d_0) - 10\phi \log_{10}(\frac{d}{d_0}) + X_\delta \tag{8}$$

In the process of simulation, the most commonly used evaluation standard is position error calculated by the Eq. (9), where (x_i, y_i) is the actual position of the i th tracked tag and (x_o^i, y_o^j) is the predicted position of the i th tracked tag.

$$\text{error}_i = \sqrt{(x_i - x_o^i)^2 + (y_i - y_o^i)^2} \tag{9}$$

4.2 Reader deployment performance

We use the PSO algorithm to optimize the deployment position of the reader. Fig.4 shows the initial deployment of the reader. Fig.5 shows the deployment of the reader after optimization.

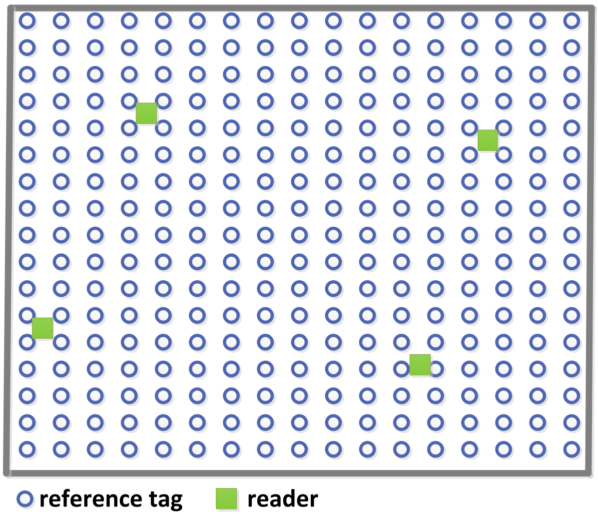

Fig.5 Optimize the deployment of the reader.

After optimizing the position of the reader through the PSO, the signal strength vectors of the reference tags and their corresponding coordinate values are used as the two inputs respectively as the training samples of the BP neural network and the PSO-BP algorithm. In addition, compared with the previous experimental results, we can get four different positioning methods as follows:

Case1: BP algorithm positioning method without reader optimization

Case2: PSO-BP algorithm positioning method without reader optimization

Case3: BP algorithm positioning method of optimizing reader deployment

Case4: PSO-BP algorithm positioning method of optimizing reader deployment The signal strength vector of the tracked tag is taken as the test input data of the BP neural network and the PSO-BP. After the model operation has been trained, the position of the tracked tag can be obtained. Fig.6 is the first 50 times the test data error comparison chart to show the preference of four different positioning methods. Fig.7 is the four positioning method of positioning error cumulative distribution function. It can be seen from Fig.10 shows that the preference of position is related to choice of algorithm and deployment of the reader. Case4: PSO-BP algorithm positioning method of optimizing reader deployment has the least overall error. Fig.7 shows the cumulative distribution function in four different cases. The abscissa indicates the positioning error, and the ordinate indicates the cumulative probability. As shown in Fig.7, the Case4 method has better positioning effect.

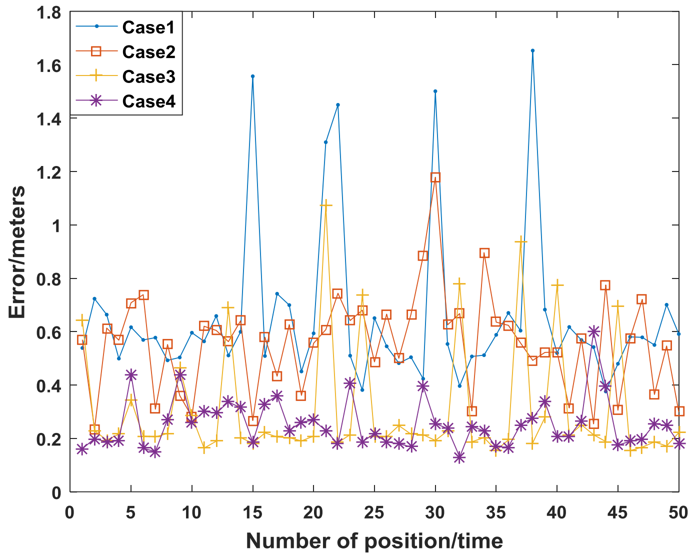

Fig.6 Comparison of four positioning methods.

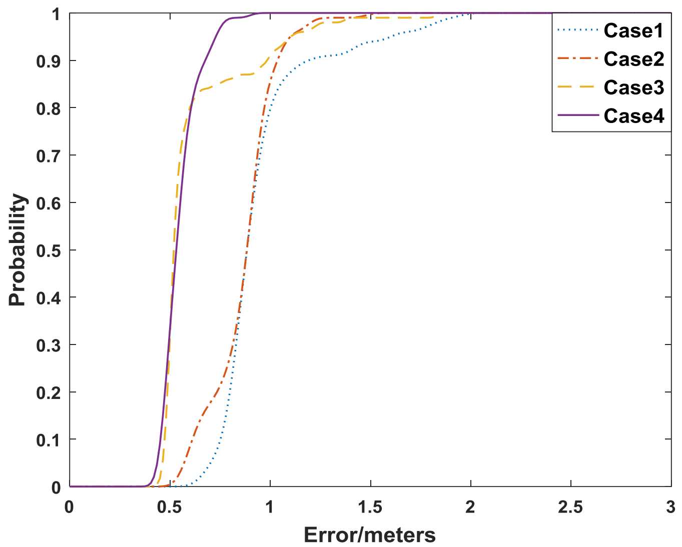

Fig.7 The cumulative distribution function of the four methods.

Table 1. Comparison of four kinds of positioning methods.

	Case1	Case2	Case3	Case4
Probability=30%	**0.8299**	**0.8142**	**0.4982**	**0.4939**
Probability=60%	**0.9130**	**0.9092**	**0.5322**	**0.5517**
Probability =85%	**1.052**	**0.9973**	**0.7398**	**0.6314**
Mean error(m)	**0.9470**	**0.8635**	**0.6047**	**0.5478**
Std.	**0.2492**	**0.1595**	**0.2308**	**0.0851**

Table 1. compares the four different positioning algorithms. As seen from Table 1, the error of PSO-BP algorithm positioning method of optimizing reader deployment is smaller than that of the other three methods at the same cumulative probability of 85%. The average error of BP algorithm positioning method of optimizing reader deployment is 0.3423m less than BP algorithm positioning method without reader optimization and the average error of the PSO-BP of optimizing reader deployment is 0.3157m less than the average error of the PSO-BP without reader optimization. Therefore, the preference of reader deployment with PSO is better than reader deployment without algorithm optimization. In addition, through the comparison of Table 1, it can be seen that using PSO to optimize BP neural network has higher positioning accuracy and better positioning stability than

BP neural network. Therefore, the fourth method has better positioning accuracy and stability than the other three methods.

5. Conclusion

In the RFID positioning, the BP neural network is directly used for positioning, and the positioning accuracy and stability of the RFID positioning needs to be improved. In addition, the positioning effect of the reader deployment based on experience is also poor. Therefore, this paper proposes to use PSO algorithm to optimize the parameters of BP neural network and reader's position respectively. On the one hand, by optimizing weights and thresholds of BP neural network, the model prediction results are avoided from getting into local optimum. On the other hand, the particle swarm optimization algorithm optimizes the deployment of readers, which improves the tolerance of signal positioning system. From the experimental results we can see that PSO algorithm to optimize the parameters of BP neural network and reader's position respectively shows an average positioning error 0.3992 m less than the average error of BP algorithm positioning method without reader optimization. This paper improves the positioning accuracy and stability from these two aspects. So the particle swarm optimization algorithm which optimizes BP neural network parameters and reader deployment is more suitable for indoor positioning.

Acknowledgments

This study was supported in part by National Science Fund for Young Scholars No.61701296, by Innovation Project of Shanghai University of Engineering Science No.17KY0202.

Authors' contributions: The study of the mobile multimedia crowd service cooperation control protocol was carried out by Shanshan Chen, and the revision of wavelet model was done by Zhicai Shi and Fei Wu. The simulation experiment and coding work were done by all the authors. This manuscript had been prepared and checked by both of the authors together. All authors read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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