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Research into a RFID Neural Network Localization Algorithm

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Abstract

The accuracy of indoor positioning algorithm has been the focus of research. In this paper, a particle swarm optimization algorithm based on particle swarm optimization algorithm and $K-means$ algorithm is proposed. In this paper, firstly, the indoor positioning RFID model is constructed, and the positioning equation is constructed, then reduce the clustering algorithm to avoid human interference, through the $K-means$ algorithm to form a particle swarm algorithm to initialize the particle swarm algorithm, finally, the particle swarm optimization algorithm is used to train all the parameters of RBF neural network, and then the optimal output model is obtained. Simulation results show that the algorithm can effectively improve the positioning accuracy, reduce energy consumption, and improve the positioning accuracy of 10%.

***Keywords**: RFID, Indoor Positioning, Subtractive Clustering Algorithm, $K-means$ RBF*

1. Introduction

Radio frequency technology is one of the key research techniques in the Internet of things. It is widely used in the identification and marking of object identity, and has a wide range of applications in intelligent home, logistics management and so on [1]. Especially in recent years, widely used in indoor positioning, has made a lot of research results [2]. Domestic and foreign scholars on the research, the literature [3] proposed using RFID topology network positioning algorithm to improve the level of automation of the refueling system. This algorithm not only can monitor the object in real time, but also can detect the working state of the reader. When the reader fails, it can still track the object, which has good robustness; an indoor localization algorithm based on neural network and RFID is proposed in the paper, which is a fusion of the literature [4] and neural network. First calculated the received signal strength of the room, then the received signal strength as the input vector of the neural network, path loss coefficient as the target output of the neural network, through the training of neural network set up indoor field strength signal propagation model, and genetic algorithm is used to optimize the parameters of the neural network; Finally, the indoor positioning performance is tested and analyzed with concrete examples. Simulation results show that the proposed algorithm can improve the indoor positioning accuracy, and can effectively meet the requirements of indoor wireless location; A RFID indoor localization algorithm based on BP neural network is proposed in the paper. The algorithm is introduced into the literature [5] neural network to establish the model of the field strength signal transformation by using the BP neural network. In the model, the input received signal strength value, output path loss coefficient, network model to improve the accuracy of the path loss coefficient, and then use the distance - loss model to achieve accurate positioning, thereby reducing the positioning error; The literature [6] proposes an improved nearest neighbor algorithm, which is the best choice to achieve the nearest neighbor label by the selection of adjacent

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reference tags; The literature [7] proposed to use the label position distribution characteristic as prior information to improve the positioning accuracy, based on time of arrival (TOA) two-step weighted least squares method from maximum likelihood estimation is extended to minimum mean square error estimation is deduced, and based on the minimum mean square error estimation of TOA location method of the Cramer Rao lower bound (CRLB) and variance theory simulation experiment proves that the algorithm has good positioning effect; The literature [8] proposed the use of fractional Fourier transform-based peak search ESPRIT algorithm localization algorithm for signal detection and estimation of azimuth multi-target non-uniform antenna array low. Simulation results show that the proposed algorithm can identify multiple frequency and space targets with high accuracy. TDOA hyperbolic positioning method is proposed in the literature [9]. The method uses radio frequency signal TDOA to measure the distance between the radio frequency (RF) tag and the target with the precise time difference, and then uses the hyperbolic location algorithm to locate the target.

Based on the above research, this paper proposes a combination of particle swarm optimization algorithm and $K-means$ algorithm based on particle swarm optimization algorithm. Firstly, the indoor positioning RFID model is constructed, and the positioning equation is constructed, then the algorithm is used to avoid human disturbance, and the initial solution of the particle swarm algorithm is generated by the $K-means$ algorithm. Finally, the all parameters of particle swarm algorithm are used to train the RBF neural network, so as to obtain the output optimization model to determine the location of RFID tags, simulation experiments show that this algorithm effectively improves the positioning accuracy.

2. Indoor Positioning RFID Model

In the indoor three-dimensional space, this paper uses the location probability distribution density to describe the position of the RFID Reader:

$$p_X^{(0)}(\boldsymbol{X}) = K_X \sum_{i=1}^{N_T} \alpha_i \cdot \delta(\boldsymbol{X} - \boldsymbol{X}_i) \tag{1}$$

In the formula, N_T is the target number; x indicates the location of the reader in the region; K_X is the normalized coefficient; α_i is the reliable factor for the position $\boldsymbol{X}_i$; $\delta(\bullet)$ is the Dirac function.

In RFID reader signal the signal collecting process, due to the noise in the signal, deformation and nonlinear, so in order to facilitate the research, hypothesis RFID reader to collect signal positioning data Z, where the RFID reader position function can describe as:

$$\begin{cases} f_X(\boldsymbol{X}/\boldsymbol{Z}) = K_X \sum_{i=1}^{N_T} \alpha_i \cdot g_{\boldsymbol{X}_i/\boldsymbol{Z}}(\boldsymbol{X} - \hat{\boldsymbol{X}}_i^{(s)}) \\ \boldsymbol{z}_m = \boldsymbol{h}_m(\boldsymbol{X}_e) + \boldsymbol{v}_m \end{cases} \tag{2}$$

In the formula, $\hat{\boldsymbol{X}}_i^{(s)} = \hat{\boldsymbol{X}}_i^{(s)}(\boldsymbol{Z}),\ i = 1, \cdots, N_T$ is the estimated result of $\boldsymbol{X}_i$; $g_{\boldsymbol{X}_i/\boldsymbol{Z}}(\boldsymbol{X} - \hat{\boldsymbol{X}}_i^{(s)})$ is the maximum value of $\boldsymbol{X}_i$ at $\boldsymbol{X} = \hat{\boldsymbol{X}}_i^{(s)}$;

In formula (2), z can be described as a combination of multiple independent position vectors:

$$\boldsymbol{Z} = \left[\boldsymbol{z}_1, \boldsymbol{z}_2, \cdots, \boldsymbol{z}_M\right]^{\mathrm{T}} \tag{3}$$

Because the signal will inevitably contain other factors such as noise, the RFID vector can be described as:

$$\boldsymbol{z}_m = \boldsymbol{h}_m(\boldsymbol{X}_e) + \boldsymbol{v}_m \tag{4}$$

Among them, $\boldsymbol{h}_m(\boldsymbol{X}_e)$ is a deterministic function vector of the RFID electronic label position $\boldsymbol{X}_e$; $\boldsymbol{v}_m$ is the positioning error vector of the vector $\boldsymbol{v}_m$.

3. Constructing the Positioning Equation

Located in the observation position: $\boldsymbol{X}_R = [0,0,0]^T$, RFID tag and RFID reader location are: $\boldsymbol{X} = [x, y, z]^T$ and $\boldsymbol{X}_{Tr}^k = [x^k, y^k, z^k]^T$, positioning system as shown in Figure 1.

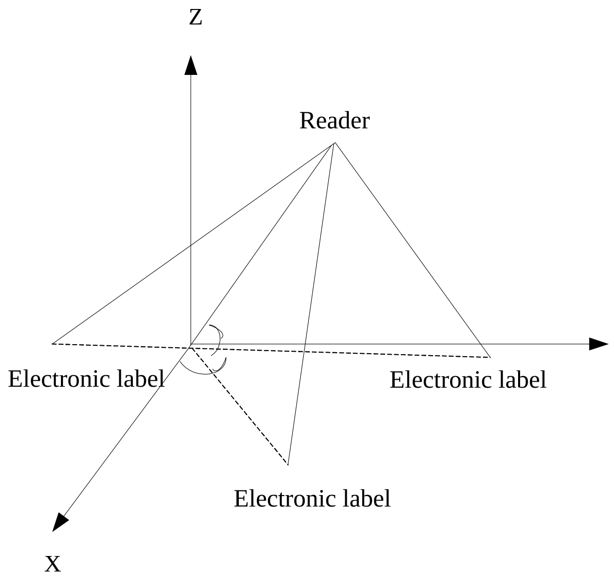

Figure 1. RFID Indoor Location

The observation equation is established according to the information of the target angle:

$$\theta = \arctan(y/x) \Leftrightarrow x\sin(\theta) = y\cos(\theta) \tag{5}$$

Because there are some errors in the positioning process, there are:

$$\theta_m = \theta + v_\theta \tag{6}$$

can get:

$$\begin{aligned} & x\sin(\theta_m) - y\cos(\theta_m) \\ &= x\sin(\theta) + x\cos(\theta)v_\theta - y\cos(\theta) - y\sin(\theta)v_\theta \\ &= x\sin(\theta) - y\cos(\theta) + \left[x\cos(\theta) + y\sin(\theta)\right]v_\theta \end{aligned} \tag{7}$$

From Figure 1:

$$R_2 = \sqrt{x^2 + y^2} = x\cos\theta + y\cos\theta \tag{8}$$

Constructing the observation equation of pitch angle:

$$\varphi = \arctan\left(z \Big/ \sqrt{x^2 + y^2} \right) \tag{9}$$

On $x\cos\theta_m + y\cos\theta_m$ at θ Taylor launched available:

$$\begin{aligned} & x\cos(\theta_m) + y\sin(\theta_m) \\ &= x\cos(\theta) - x\sin(\theta)v_\theta + y\sin(\theta) + y\cos(\theta)v_\theta \\ &= R_2 + \left[y\cos(\theta) - x\sin(\theta) \right] v_\theta = R_2 \end{aligned} \tag{10}$$

Then the formula (9) is:

$$x\cos\theta_m \sin\varphi_m + y\sin\theta_m \sin\varphi_m - z\cos\varphi_m = R_2 \sin\varphi_m - z\cos\varphi_m \tag{11}$$

The observation equation of pitch angle becomes:

$$x\cos(\theta_m)\sin(\varphi_m) + y\sin(\theta_m)\sin(\varphi_m) - z\cos(\varphi_m) = Rv_\varphi \tag{12}$$

According to the relation of time difference, the equation is constructed:

$$\tau^k = (R + r^k - d^k)/c \tag{13}$$

$$\begin{aligned} & R^2 - (r^k)^2 = (R + r^k)(R - r^k) \\ &= 2x^k x + 2y^k y + 2z^k z - (x^k)^2 - (y^k)^2 - (z^k)^2 \end{aligned} \tag{14}$$

The formula (13) into the formula (14), and formula (13) can be obtained:

$$R = \frac{x^k x + y^k y + z^k z}{c\tau^k + d^k} - \frac{(d^k)^2}{2(c\tau^k + d^k)} + \frac{1}{2}(c\tau^k + d^k) \tag{15}$$

Finally, establish the positioning equation:

$$\tau_m^k = \tau^k + v_\tau \tag{16}$$

The localization of RFID is a typical nonlinear estimation problem, and it is difficult to establish a precise target location model based on the traditional method. In order to improve the positioning accuracy, the particle swarm optimization algorithm is used to optimize the parameters of RBF neural network in this paper.

4. PSO-RBF Neural Network Model

RBF neural network has the advantages of simple structure, fast convergence, easy implementation and strong robustness. The RBF neural network usually consists of 3 layers: input layer, hidden layer and output layer. PSO algorithm has not only the ability of global optimization, but also local optimization. In this paper, we use the subtractive clustering algorithm to determine the number of RBF center points, determine the initial solution of the particle swarm by $K-means$ method, and use the PSO algorithm to train the Gauss's function in the RBF neural network, and the hidden layer and output layer weights.

4.1. Subtractive Clustering Algorithm

In this method, each data sample is used as the center of the class, and the cluster centers can be determined according to the density of the sample data, and the distribution of the effective feedback data can be effectively. When there are SS data samples in the DDD dimensional space of the data samples for each data point, the density formula is

$$D_i = \sum_{j=1}^{M} \exp(-\frac{\| x_i - x_j \|^2}{(\lambda / 2)^2}) \tag{17}$$

In formula (17), i, j, respectively, said two data samples, λ density index. Select the highest density point as the first cluster center, the density is marked as SS, update the density index of each data point:

$$D_{c1} = D_i - \sum_{j=1}^{M} \exp(-\frac{\| x_i - x_{cs} \|^2}{(\lambda / 2)^2}) \tag{18}$$

After the update of the density index, select the next cluster center x_{c2}, continuous iteration, to meet the end of the $D_{\max} < D_{c1}\lambda$ clustering.

4.2. $K-means$ Algorithm

From a data object where a collection of randomly selected data objects, each object said a clustering center and by other data object and the data objects, where the clustering center distance continuous the remaining data center gives to the center of the nearest class, and update new data objects are added to the existing data center, we in the process iteratively, until meet the class center does not change so far.

4.3. Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) algorithm is an intelligent algorithm, mainly used to group flight simulation of birds foraging behavior, in d-dimensional search space, the position and velocity of the i particle ($i = 1, 2, \cdots, m$) respectively, $\mathbf{Z}_i = (z_{i1}, z_{i2}, \cdots, z_{iD})$, $\mathbf{V}_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$, P_{id}, indicated optimal positions in the history of the i particle "flight", p_{gd} said population history best position, the particle update the velocity and position according to the following formula:

$$\begin{aligned} v_{id}(t+1) &= \omega \times v_{id}(t) + c_1 \times rand() \times \left(p_{id}(t) - z_{id}(t)\right) \\ &\quad + c_2 \times rand() \times \left(p_{gd}(t) - z_{id}(t)\right) \end{aligned} \tag{19}$$

$$z_{id}(t+1) = z_{id}(t) + v_{id}(t+1) \tag{20}$$

Among them, T represents the number of iterations; C1, C2 for learning factors; rand () is a random number between [0, 1]; ω is the inertia weight.
In this paper, the inertia weight is updated by linear change:

$$\omega = t + \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} \tag{21}$$

Among them, $\omega_{\max}$ is the initial weight; $\omega_{\min}$ is the final weight; $t_{\max}$ is the maximum number of iterations; t is the current iteration number.

4.4. PSO-RBF Algorithm Model

(1) Select a sample size, as the sample point, the sample according to the formula (22) for normalization, the sample size of the data between [0, 1]

$$x_i = 1 - \frac{x_i}{x_{\max} - x_{\min}} \tag{22}$$

(2) According to the formula (17) calculated the density of data points, while searching for the $\max\{D_1, D_2, \cdots D_M\}$ data points as the first clustering center and the density index is obtained according to the formula (18), find the $D_{\max}$, and conversely if not found, continue to look for, until he found so far. Determine the number of cluster centers.

(3) The number of cluster centers will be generated as the number of $K-means$ clustering, and then perform the $K-means$ algorithm to generate a set of cluster centers, the results generated in the first k clustering for $C_{k1}, C_{k2}, \cdots C_{kn}$, and constantly iteration, until the K times. At the end of the cluster, the initial population size of the particle swarm algorithm is $K-means$, and the initial population size of the particle swarm algorithm is K, which needs to be K clustering, which can produce K initial particles.

(4) Will have the K group basis function centers, and randomly generated K a RBF neural network weights w_i, Gaussian radius function r combination of ($C_{k1}, C_{k2}, \cdots C_{kn}, w_{p1}, w_{p2}, \cdots w_{pk}, r_p$), produced a total of a K the structure of particle swarm algorithm as initial solution, through the continuous adjustment of the particle velocity and quality, when meet iteration termination condition time, the end of the iteration to determine all the parameters of RBF function.

5. Target Location Algorithm based on PSO-RBF

In the actual scene, for nonlinear relationships exist in RFID electronic tag target position and the position information field and RBF is nonlinear approximation ability and can therefore PSO-RBF is adopted to establish a position information field to the target location mapping model, the steps are as follows

Step1: The information field data of the target position of the RFID electronic tag is collected and used as an input, the actual position of the target is used as the output, and the sample is constructed through the input and output.

Step2: The training samples are input to the RBF for learning, and the particle swarm optimization algorithm is used to optimize the RFB parameters, and the nonlinear estimation model of the target position and position information field of FRID is obtained.

Step3: The signal input to the RFID electronic tag to be positioned to establish a nonlinear estimation model, the estimated position of the output model.

The Flow Chart of the Algorithm is shown in Figure 2.

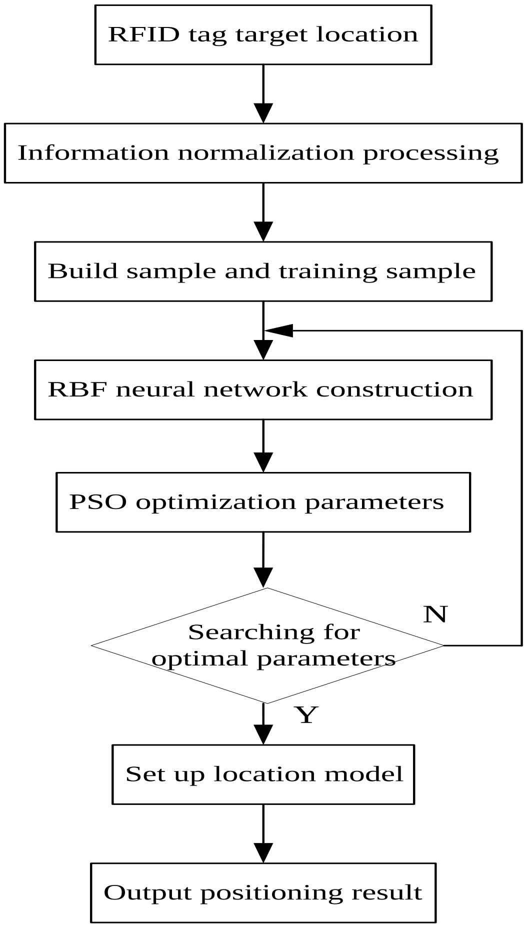

Figure 2. Algorithm Procedure

6. Simulation Experiment

In order to further test the superiority of this algorithm, we set up 3 sets of experiments, each set of 5 electronic tags, and select the 30*30m in the three-dimensional space for the experiment.

Table 1. Experimental Data

The experimental group No.	Tag No.	coordinates	coordinates	coordinates
Experiment 1	1	1.07	2.52	0.52
	2	2.33	1.72	2.07
	3	1.82	2.35	1.82
	4	3.79	5.29	4.21
	5	4.71	5.23	3.12
Experiment 2	1	8.22	9.81	8.12
	2	10.43	12.61	13.78
	3	15.78	18.42	16.23
	4	17.52	18.41	18.23
	5	15.71	17.89	17.72
Experiment 3	1	22.12	23.79	28.62
	2	28.61	22.21	29.12
	3	20.42	25.51	22.61
	4	23.72	24.21	26.12
	5	27.61	25.13	23.78

Because in the actual environment due to the occurrence of interference, so obtained a large data exists certain noise, the algorithm in the literature [10] in the course of the study considered these factors, will compare the algorithm with reference [10] algorithm. Therefore, comparing the results with the practice. The comparison results are shown in Figure 3-4. Figure 5-7 describes the error contrast of the 5 tab points in the three groups.

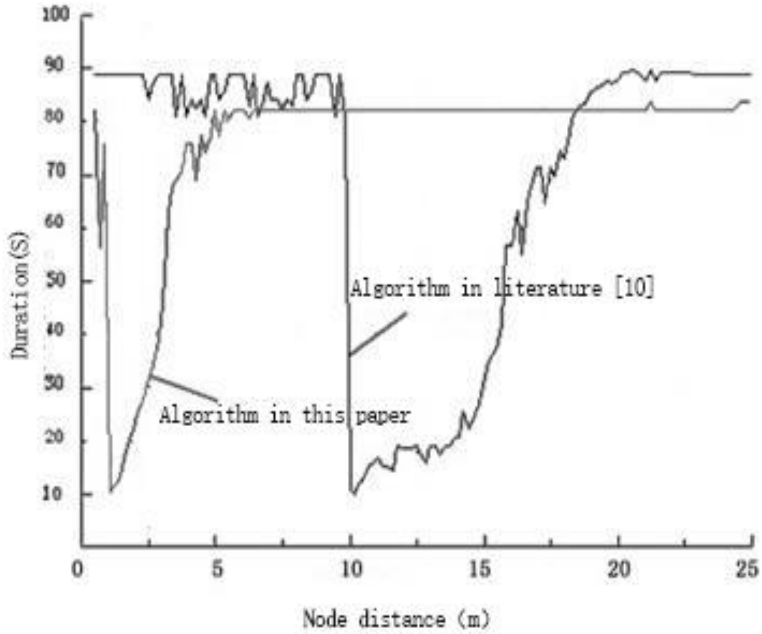

Figure 3. Comparison of Two Localization Algorithms' Duration Time

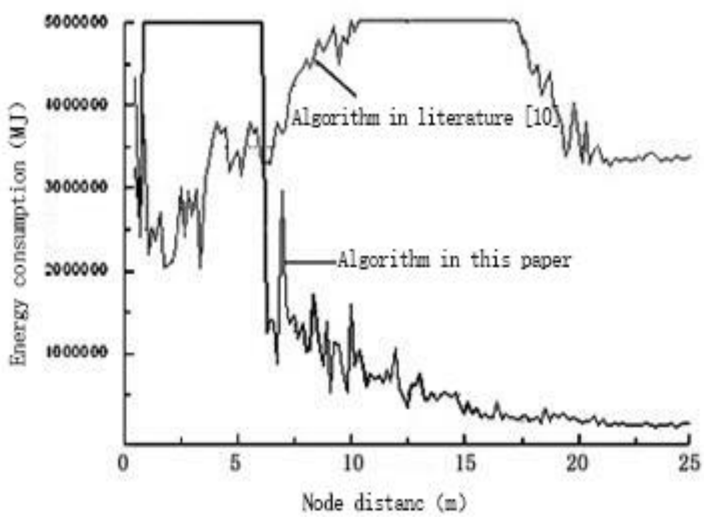

Figure 4. Comparison of Two Localization Algorithms' Energy Consumption

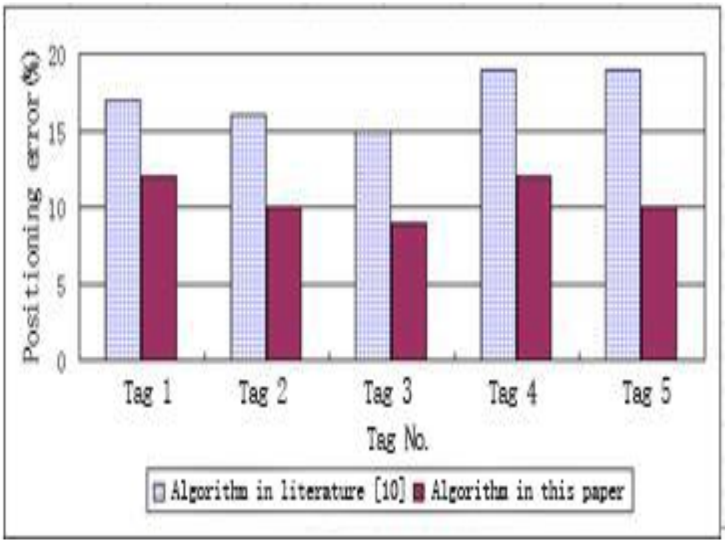

Figure 5. Comparison of Label Positioning in the First Experiment

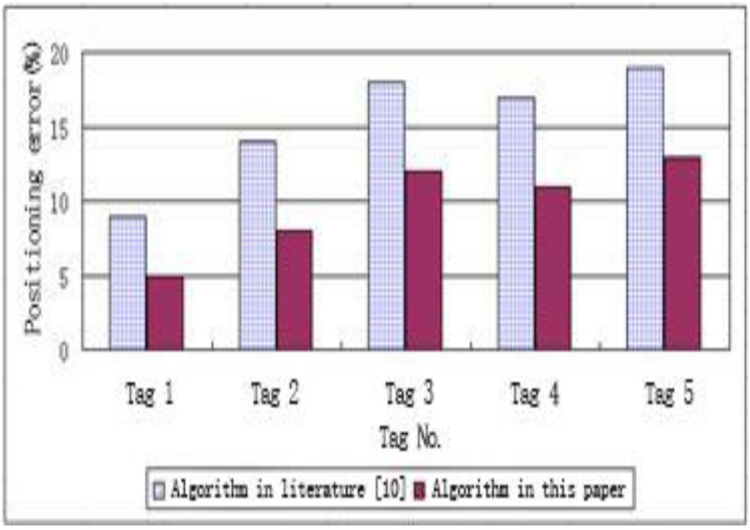

Figure 6. Comparison of Label Positioning in the Second Experiment

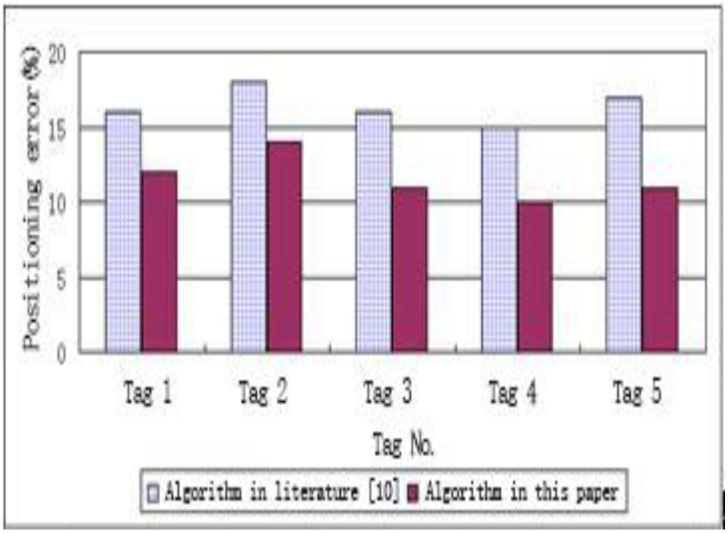

Figure 7. Comparison of Label Positioning in the third Experiment

It can be found in Figure 3-4, compared to algorithm proposed in this paper and the authors algorithm both in positioning time consumption and energy consumption are reduced, mainly due to the location equation is constructed using the PSO-RBF algorithm, so that the positioning is more accurate. Compared with the three sets of data in Figure 5-7, the algorithm in this paper is reduced by 10% to 6% compared with the literature algorithm, which shows that the algorithm can effectively improve the RFID positioning accuracy.

7. Conclusion

How to improve the positioning accuracy of RFID has been the focus of the study, this paper firstly constructs indoor positioning RFID model, and then constructs the positioning equation. In this paper, the particle swarm optimization algorithm is used to optimize the parameters of RBF neural network, which can improve the accuracy of positioning by reducing the clustering algorithm and SS algorithm. Simulation results show that the algorithm can effectively improve the positioning accuracy of 10%.

References

[1] Q. Z. Hong, "Internet of Things-oriented wireless sensor networks review", Journal of Electronics and Infornation technology, vol. 35, no. 1, **(2013)**, pp. 215-2227.
[2] L. L. Na, "Summary of study on RFID Indoor localization technology", International Journal of Computer Applications and Software, vol. 32, no. 9, **(2015)**, pp. 1-4.
[3] X. Xiang, "Application of node localization algorithm for RFID topology network", Journal of Liaoning Technical University （Natural Science Edition, vol. 34, no. 2, **(2015)**, pp. 244-248.
[4] Z. Kai, "Indoor Localization Algorithm Based on BP Neural Network and RFID", Journal of Laser Applications, vol. 36, no. 8, **(2015)**, pp. 138-141.
[5] W. Chao, "Research on RFID Indoor Localization Algorithm Based on BP Neural Network", Journal of Computer Simulation, vol. 32, no. 7, **(2015)**, pp. 323-326.
[6] S. Y. Bo, "Research of RFID Indoor Location Algorithm Based on Reference Tags", Journal of Video Engineering, vol. 39, no. 1, **(2015)**, pp. 109-112.
[7] L. Yi, "Minimum mean square error estimator for Indoor Mobile Location Using RFID Technique", Journal of Nanjing University of Posts and Telecommunications(Natural Science), vol. 33, no. 6, **(2013)**, pp. 69-73.
[8] P. Yong, "A Location Method for Multi-tags of RFID by a Movable Reader Based on FRFT", Acta Scientiarum Naturalium Univsesitatis Nankaiensis, vol. 46, no. 5, **(2013)**, pp. 73-78.
[9] Y. G. Hua, "RFID hyperbolic positioning using TDOA method for indoor moving target", Journal of Computer Applications, vol. 34, no. 2, **(2013)**, pp. 52-54.
[10] C. Z. Qiang, "An RFID Indoor location algorithm based on fuzzy neural network model", Journal of Systems Science and Mathematical Sciences, vol. 34, no. 12, **(2014)**, pp. 1438-1450.

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