# RFID Indoor Positioning Based on RBF Interpolation and QPSO

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*Abstract:* Aiming to reduce the drawbacks of traditional VIRE approach, such as inaccurate boundary positioning and poor results of virtual tags using linear interpolation, we propose a new algorithm based on Radial Basis Functions (RBF) interpolation method and Quantum-behaved Particle Swarm Optimization (QPSO) in this paper. In order to simulate the actual loss of RSSI better, the proposed approach uses smooth global RBF interpolation. In addition, QPSO is introduced to estimate the coordinates of tracking tags by conducting the objective function under optimized concepts. Numerical simulated experiments show that the general accuracy of the new method is approximately 0.167 meters, enjoying 84.5% increase compared to VIRE algorithm. Therefore, this approach has a relative high positioning precision.

*Key-Words:* - RFID, Indoor Positioning Algorithm，RBF，QPSO

## 1 Introduction

Indoor positioning technologies are paid closer attention increasingly concerned with the development of the Internet of Things, especially in indoor environments such as warehouses, libraries, etc. With its fast and accurate position, it benefits the achievement of safety management through location information. Among the several common indoor positioning technologies, RFID positioning system is easy to set up with lower cost and higher precision, which is widely applied in many fields [1].

In order to achieve fast and accurate positioning, better positioning algorithm with high precision and rapid response is highly demanded besides promoting the hardware of RFID positioning system. Many scholars were struggled to study the RFID positioning algorithms, which are able to estimate the location of tracking tags more quickly and more accurate. LIONEL M.Ni (2004) [2] came up with the LANDMARC approach, in which the expensive fixed readers are substituted by several reference tags to assist positioning. The LANDMARC system not only lowers the cost, but also improves dynamic performance of the system. However, it has drawbacks such as severe radio signal multi-path effects in closed environment and multi-redundant computations, etc. Under the premise of not promoting any hardware device, Zhao (2007) [3] proposed the VIRE approach, in which virtual tags were introduced through Virtual Grid Coordinate Determination. The RSSI values of virtual tags are calculated through linear interpolation according to the RSSI values of reference tags. Also, a new concept called Proximity Map is used to estimate the coordinates of tracking tags. The method helps RFID positioning system cost less for the reason that it uses fewer reference tags. What is more, it gains higher precision at the same time. However, it causes errors when calculating the RSSI values of virtual tags through linear interpolation. Furthermore, using the Proximity Map to estimate positions of tracking tags, the accuracy of the RFID system will be influenced by the fixed threshold. To reduce the drawbacks of VIRE approach, Wen (2014) [4] advanced that Standard Particle Swarm Optimization (PSO) replaces Proximity Map and weighting factors setting. The ratio of Euclidean distance and the number of readers is set as the fitness function. Therefore, the optimal solution of tracking tags can be gained through an iterative search. At the meantime, regionalized Lagrange polynomial is put forward to substitute linear interpolation method. However, in the process of calculating weights, the situation that the denominator is zero in the interpolation formula will appear, under the circumstance that at least two reference tags have the same distance from the same reader in the positioning area, causing the problem of unable location. As matter of fact, the case usually happens in real practice. Additionally, the standard PSO algorithm has a defect that it doesn't guarantee a global convergence in probability, which means that it may diverge or fall into local optima in the searching process [5,6]. Obviously, it is not allowed on important occasions such as the monitoring of radioactive source. Therefore, we come up with a new method which is able to improve the VIRE approach based on Radial Basis Functions (RBF) interpolation method and Quantum-behaved Particle Swarm Optimization (QPSO), obtaining a RFID localization algorithm with higher positioning accuracy and better stability.

# 2 Related work

## 2.1 The process of RFID indoor positioning algorithm of RBF-QPSO

Figure 1 shows the flowchart of RFID positioning algorithm based on RBF-QPSO. It includes placing several reference tags and stationary readers; designing the RFID positioning model; collecting the RSSI values of reference tags and tracking tags; creating virtual tags in the positioning area, and setting up a mathematical model of the RSSI values virtual tags based on RBF interpolation method according to the RSSI values of reference tags; setting virtual tags as particles, and establishing the model of quantum particle swarm optimization to estimate the coordinates of tracking tags by several iterations.

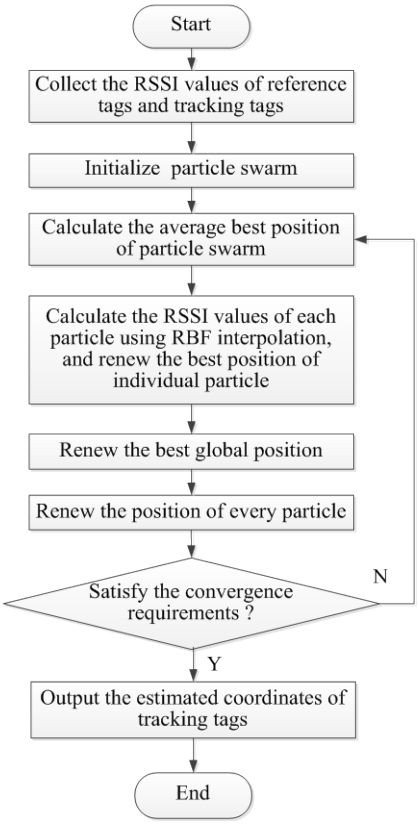


Fig. 1. The flowchart of RFID positioning algorithm based on RBF-QPSO

## 2.2 The RBF-QPSO approach

Suppose the number of reference tags is $N$ and that of fixed readers is $K$. All of them are placed in the positioning area. Assume the number of tracking tags is $Q$ and that of virtual tags is $M$. The RSSI value of the $n$-th reference tag shown on the $k$-th reader is $\theta_{kn}(1 \le k \le K, 1 \le n \le N)$, while the RSSI value of the $q$-th tracking tags is $S_{kq}(1 \le k \le K, 1 \le q \le Q)$.

### 2.2.1 The RSSI values of virtual tags calculated using RBF interpolation

In VIRE approach, linear interpolation is used to measure the virtual tags. However, this approach is not able to satisfy the high demand of stimulating the non-linear RSSI loss. Therefore, researchers have been making a lot of improvements to the interpolation of virtual tags for a long time. Shao (2013) [7] pointed out interpolation function based on the two-dimension Newton interpolation approach, which enjoys high precision but costs large amount of operations. Wan (2014) [8] came up with a method that calculates the values of RSSI of virtual tags by dividing the positioning area into several blocks, but the accuracy is not high enough. Wen (2014) [4] proposed regionalized Lagrange interpolation, yet the situation that denominator is zero in the interpolation formula will appear in this approach.

As one of the most accurate interpolation methods, Radial Basis Function (RBF) has been widely used in many fields [9,10]. With the application of Radial Basis Functions global interpolation, all the information of the reference tags collected can be concerned. Thus smooth non-linear RSSI loss can be created. This advantage will be more obvious especially the number of reference tags is huge in a large-scale indoor place.

This approach conducts Zero-order Normalization based on the Compactly Supported RBF pointed out by Wendland (1995) [11]. According to the RSSI values of reference tags, the RSSI $T_{km}(1 \le k \le K, 1 \le m \le M)$ of every virtual tag can be calculated using the RBF interpolation by the formula:

$$T_{km} = \sum_{i=1}^{N} g_i(x_m, y_m) \bullet \alpha_i \tag{1}$$

$$g_i(x_m, y_m) = \frac{D_i(x_m, y_m}{\sum_{i=1}^{N} D_i(x_m, y_m)}, D_i(x_m, y_m) = (\max(0, 1 - r_{mi}))^4 \bullet (4r_{mi} + 1)$$

is the radial basis function; $\alpha_i$ is the weight function which is in correspondence to every radial basis function; $r_{mi} = \frac{\sqrt{(x_m - x_i)^2 + (y_m - y_i)^2}}{d_{sp}}$, $d_{sp}$ is the constant, representing the radius of the radial basis function. $x_i, y_i$ are reference tag coordinates, $1 \le i \le N$ ; $x_m, y_m$ are virtual tag coordinates, $1 \le m \le M$ .

Formula (1) can be express as a matrix representation as follows.

$$T = G\alpha \tag{2}$$

In formula (1), the sample point is the coordinate of the reference tag. If the center of every radial basis function is reference tag coordinate, and we put it into the radial basis function, the matrix G will be a fixed function as shown below.

$$T_0 = G_0\alpha = \begin{bmatrix} g_1(x_1, y_1) & g_2(x_1, y_1) & \cdots & g_N(x_1, y_1) \\ g_1(x_2, y_2) & g_2(x_2, y_2) & \cdots & g_N(x_2, y_2) \\ \vdots & \vdots & \ddots & \vdots \\ g_1(x_N, y_N) & g_2(x_N, y_N) & \cdots & g_N(x_N, y_N) \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix}$$

The RSSI values of the reference tags are $T_0 = \theta_0 = \left[\theta_{k1}, \theta_{k2}, \cdots, \theta_{kN}\right]^T$ . Therefore, according to formula (2), the weight $\alpha$ is given by

$$\alpha = G_0^{-1}T_0 = G_0^{-1}\theta_0 \tag{3}$$

Put formula (3) into formula (1) we get the RSSI values of the virtual tags using the following equation:

$$T_{km} = [g_1(x_m, y_m), g_2(x_m, y_m), \cdots, g_N(x_m, y_m)] \bullet G_0^{-1} \bullet \theta_0$$

### 2.2.2 Coordinates estimation based on QPSO

In order to solve the problem that PSO is not able to guarantee a global convergence in probability, Sun [12] proposed QPSO algorithm based on Quantum Mechanics. The advantages of this algorithm are obvious. To begin with, the algorithm will not diverge infinitely and its speed of convergence is fast. In addition, compared to PSO, the algorithm parameters needed to be adjusted is fewer. In the RFID position monitoring of radioactive source, the system should not only enjoy a high level of stability, but also should be easy to establish and response quickly. In comparison to PSO, QPSO has strict proof of convergence. Besides, its demand for artificially modified parameters is lower and its speed of optimization is faster. Together they make it an ideal optimized algorithm.

The objective function is defined as follow:

$$f(x_m, y_m) = \frac{E_k}{K} = \frac{\sqrt{\sum_{k=1}^{K}(T_{km} - S_{kq})^2}}{K} \tag{4}$$

Equation (4) means the ratio of Euclidean distance from virtual tags to tracking tags and the number of readers. The smaller $f(x_m, y_m)$ is, the position of virtual tag ($x_m$,$y_m$) and tracking tag ($x_q$,$y_q$) is nearer. During the estimation, the particle colony is composed of $M$ virtual tags, which is expressed as $X(t) = \left\{X_1(t), X_2(t), \cdots, X_M(t)\right\}$ . In the two-dimension search space, the design variables of virtual tags are $x_m$ and $y_m$, thus the position of the $m$-th particle at the $t$-th moment is $X_m(t) = \left[x_m(t), y_m(t)\right], i = 1, 2 \cdots M$ .

$P_m(t) = \left[P_{m,1}(t), P_{m,2}(t)\right]$ represents the best position of the particle, while $G(t) = \left[G_1(t), G_2(t)\right]$ means the best global position. Besides, $G(t) = P_g(t), (1 \le g \le M)$ , $g$ represents the serial number of particle which enjoys the best global position.

At the time when $t$=0, we initialize the position $X_m(0)$ of every particle in swarm and set the best position of individual particle using the equation $P_m(0) = X_m(0)$.

The average best position of particle swarm can be calculated by the equation $C_j(t) = \frac{1}{M}\sum_{m=1}^{M} P_{m,j}(t)$ . For every particle in the swarm, the objective function of the present position can be calculated by equation (4). Besides, the best position of individual particle is renewed using the following equation:

$$P_m(t) = \begin{cases} X_m(t) & \text{if } f\left[X_m(t)\right] < f\left[P_m(t-1)\right] \\ P_m(t-1) & \text{if } f\left[X_m(t)\right] \ge f\left[P_m(t-1)\right] \end{cases}$$

In addition, the best global position of particle swarm is renewed which is given by

$$G(t) = \begin{cases} P_m(t) & \text{if } f\left[P_m(t)\right] < f\left[G(t-1)\right] \\ G(t-1) & \text{if } f\left[P_m(t)\right] \ge f\left[G(t-1)\right] \end{cases}$$

At last, the position of every particle is renewed by the formula:

$$X_{m,j}(t+1) = p_{m,j}(t) \pm \alpha \bullet |C_j(t) - X_{m,j}(t)| \bullet \ln\left[1/u_{m,j}(t)\right],$$

$u_{m,j}(t) \sim U(0,1)$ .

$$p_{m,j}(t) = \varphi_j(t) \bullet P_{m,j}(t) + \left[1 - \varphi_j(t)\right] \bullet G_j(t),$$

$\varphi_j(t) \sim U(0,1)$ .Therefore we can get the position of virtual tags of the new generation.

Repeat the above operations and continue the iterations until all the convergence requirements are satisfied, the best position of the particle is the estimated coordinate of the tracking tag at this time.

# 3 Experimental setup

## 3.1 Evaluation of the RFID positioning algorithm

Root-mean-square error (RMSE) is standard error. In limited number of times of measurement, RMSE is usually obtained as $e=\sqrt{\sum_{j=1}^{n} d_j^2/n}$. $N$ is the number of times of measurement, while $d_j$ is the deviation of measured value and real value. In positioning algorithm, $d_j=\sqrt{(x_j-x_0)^2+(y_j-y_0)^2}$. $(x_j, y_j)$ is the estimated coordinate of $j$-th tracking tag. $(x_0, y_0)$ is the real coordinate of the tracking tag. Therefore, the estimation error e is defined as $e=\sqrt{\sum_{j=1}^{n}\frac{(x_j-x_0)^2+(y_j-y_0)^2}{n}}$.

Cumulative Distribution Function (CDF) refers to the probability that random variable is less or equal to a certain numerical value $F(x)=P(X\le x)$.In RFID positioning algorithm, CDF is introduced to describe the cumulated probability distribution of the estimation error of the tracking tags [13]. According to relevant theories of mathematical statistics, the theoretical cumulative distribution function can be substituted by empirical distribution function. The empirical distribution function is $F_n(x)=\frac{v_n(x)}{n}(-\infty<x<+\infty)$, in which $n$ means the number of the total samples, while $v_n(x)$ represents the empirical frequency of the random event $\{\xi<x\}$.

### 3.2 Analysis of RFID positioning algorithm

In order to test the performance of the algorithm, simulated experiments of different RFID positioning algorithms based on MATLAB were conducted. Figure 2 shows the RFID indoor positioning model. Suppose in the $4m\times 4m$ indoor positioning area, 16 RFID reference tags and 4 RFID fixed readers are placed. Besides, 10 tracking tags are randomly generated. The RSSI values of reference tags and tracking tags are calculated through the loss model of indoor logarithm path [14].

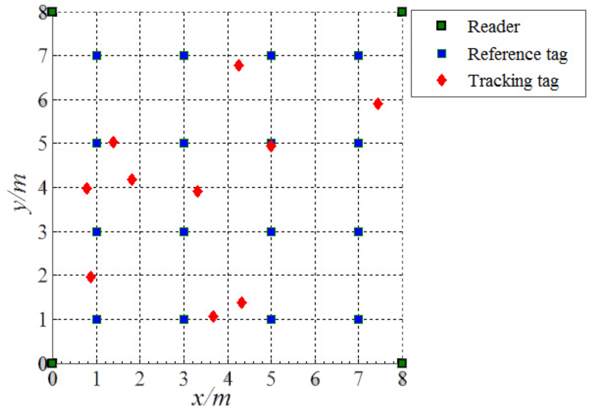


Fig.2 RFID positioning model

We used 10 random tags and conducted simulated comparison experiments respectively for the VIRE approach (Linear-VIRE), the VIRE approach based on RBF interpolation (RBF-VIRE), the VIRE approach based on PSO (Linear-PSO) [4] and the RBF-QPSO approach which we propose in this paper. Table 1 shows the comparison of estimated coordinates of tacking tags in different positioning algorithms. Table 2 shows the comparison of RMSE in different positioning algorithms. Figure 3 is the histogram of RMSE in different positioning algorithms.

Table 1 Comparison of estimated coordinates of tacking tags in different positioning algorithms

| No. | Tracking tag | Linear-VIRE | RBF-VIRE | Linear-PSO | RBF-QPSO |
|---|---|---|---|---|---|
| 1 | (1.8171,4.1805) | (2.1385,4.1865) | (2.0753,4.2988) | (2.0028,4.1364) | (1.8168,4.1486) |
| 2 | (7.4473,5.9045) | (6.5254,5.8529) | (6.7254,5.8790) | (7.0000,5.9341) | (7.3882,5.8087) |
| 3 | (5.0031,4.9372) | (5.0484,4.8246) | (5.0670,4.9139) | (4.9725,4.9350) | (5.0126,4.9223) |
| 4 | (0.8697,1.9660) | (1.6511,1.9840) | (1.2771,2.1168) | (1.0000,2.0326) | (0.9476,2.0475) |
| 5 | (4.3219,1.3886) | (4.2981,1.9051) | (4.6634,1.8441) | (4.3793,1.4319) | (4.3283,1.3475) |
| 6 | (3.3072, 3.9087) | (3.4179,3.9602) | (3.3210, 3.9761) | (3.3217,3.9313) | (3.3027,3.9098) |
| 7 | (4.2503, 6.7853) | (4.2534,6.1534) | (4.5472, 6.3116) | (4.2429,7.0000) | (4.2488,6.8404) |
| 8 | (3.6845, 1.0678) | (3.6586,1.7622) | (3.2737,1.5838) | (3.6902,1.0000) | (3.6861,1.0091) |
| 9 | (1.3835, 5.0256) | (1.8654,4.9621) | (1.7452,5.1433) | (1.2504,5.0435) | (1.4230,5.0422) |

| | | | | | |
|---|---|---|---|---|---|
| 10 | (0.7907, 3.9885) | (1.6403,3.8729) | (1.5507,3.7965) | (1.0000,3.9860) | (0.6998,3.9928) |

Table 2 Comparison of RMSE of different positioning algorithms

| No. | Linear-VIRE (m) | RBF-VIRE (m) | Linear-PSO (m) | RBF-QPSO (m) |
|---|---|---|---|---|
| 1 | 0.32144776 | 0.28405582 | 0.19087490 | 0.03190722 |
| 2 | 0.92336386 | 0.72236904 | 0.44827659 | 0.11255337 |
| 3 | 0.12137212 | 0.06798727 | 0.03067349 | 0.01763585 |
| 4 | 0.78158865 | 0.43441775 | 0.14634343 | 0.11275860 |
| 5 | 0.51707077 | 0.56930229 | 0.07191265 | 0.04156489 |
| 6 | 0.12203969 | 0.06880409 | 0.02683924 | 0.00495818 |
| 7 | 0.63189061 | 0.55908944 | 0.21482835 | 0.05508960 |
| 8 | 0.69488523 | 0.65958657 | 0.06803903 | 0.05872176 |
| 9 | 0.48607918 | 0.38033518 | 0.13432957 | 0.04284300 |
| 10 | 0.85742850 | 0.78391501 | 0.20931564 | 0.09100006 |

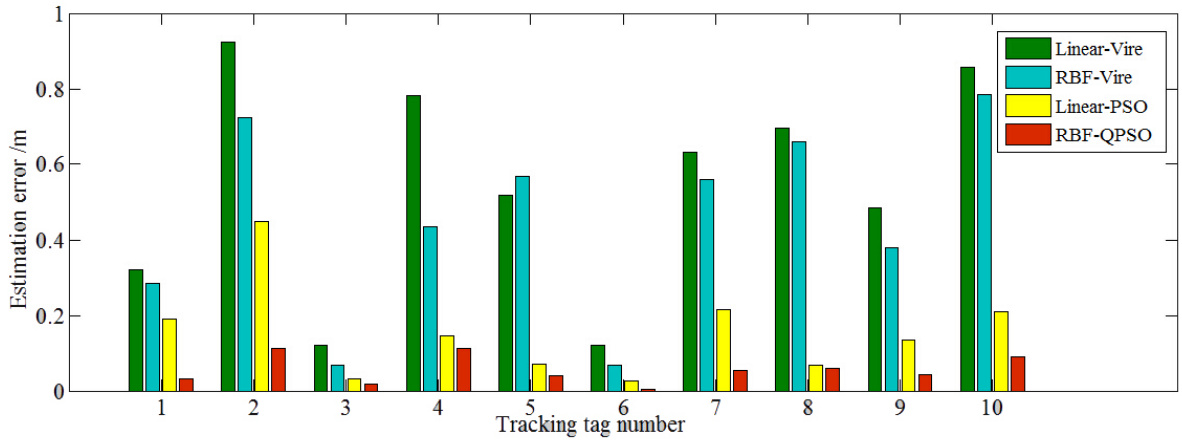


Fig.3 Histogram of RMSE errors of different positioning algorithms

From the comparison of Linear-VIRE and RBF-VIRE, under the estimation method of Proximity Map, RBF interpolation enjoys higher positioning precision compared to linear interpolation except the No.5 tag. RBF-QPSO has notable improvement in the positioning precision compared to Linear-PSO and Linear-VIRE. The increase is about 13.69%~83.28% and 85.47%~95.94% respectively.

The randomness is rather big and the confidence is not high enough, for the reason that a small amount of tags are experimented. Therefore, a large amount of tags should be randomly experimented and different algorithms should be evaluated using cumulative distribution function. In order to show the performance of the algorithm, 5000 tags were randomly produced in the positioning area in this simulated experiment. Under linear interpolation and RBF interpolation, tag coordinates were estimated using Proximity Map, PSO and QPSO. Figure 4 shows the CDF curves of different algorithms.

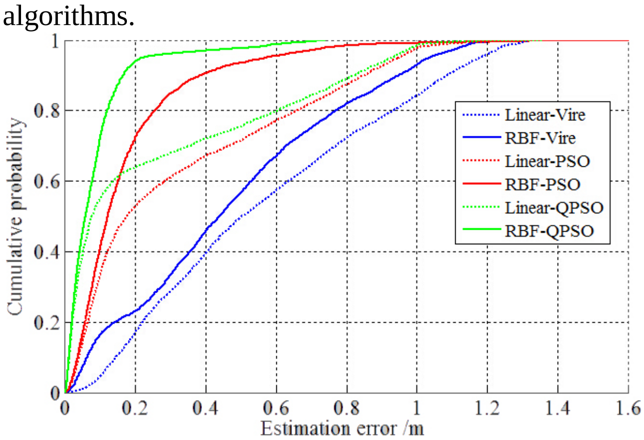


Fig.4 CDF curves of different algorithms

From the curves above, it is concluded that RBF interpolation enjoys a total higher positioning precision compared to linear interpolation under the same search method. Moreover, QPSO enjoys a notable improvement in the positioning precision compared to Proximity Map and PSO under the same interpolation method. For the 90% tags, the estimation errors of RBF-QPSO are less than 0.167 meters and that of Linear-PSO are less than 0.842 meters, while the positioning errors of Linear-VIRE are less than 1.079 meters. Compared to Linear-PSO and Linear-VIRE, the estimation precision of RBF-QPSO is increased by 80.17% and 84.52% respectively.

# 4 Conclusion and future work

This paper presented a RFID positioning algorithm with higher precision. With the application of RBF interpolation, the influence of multiple tags towards the RSSI values of virtual tags is considered, meaning that we are able to imitate the real values much better. At the same time, in big-scale indoor places with a large amount of reference tags, the interpolation is more precise due to more sample points. In comparison to PSO, the number of adjustable parameter is less. Moreover, particles can cover the whole feasible solution space thus the rate of convergence is faster and the computation is less. Experiments show that the positioning precision of RBF-QPSO approach is roughly 0.167 meters. There are 80.17% and 84.5% increase compared to Linear-PSO and VIRE respectively.

# 5 Acknowledgement

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*References:*

[1] Bekkali A, Sanson H, Matsumoto M. RFID indoor positioning based on probabilistic RFID map and Kalman filtering[C]//Wireless and Mobile Computing, Networking and Communications, 2007. WiMOB 2007. Third IEEE International Conference on. IEEE, 2007: 21-21.

[2] Ni L M, Liu Y, Lau Y C, et al. LANDMARC: indoor location sensing using active RFID[J]. Wireless networks, 2004, 10(6): 701-710.

[3] Zhao Y, Liu Y, Ni L M. VIRE: Active RFID-based localization using virtual reference elimination[C]//Parallel Processing, 2007. ICPP 2007. International Conference on. IEEE, 2007: 56-56.

[4] Wen P Z, Su T T, Li L F, Zhang J J. PSO-based RFID positioning algorithm [J]. Computer Engineering and Science ,2014,05:917-922.

[5] Van den Bergh F, Engelbrecht A P. A new locally convergent particle swarm optimizer[C]//Proceedings of the IEEE international conference on systems, man, and cybernetics. 2002, 7: 6-9.

[6] Van Den Bergh F. An analysis of particle swarm optimizers [D]. University of Pretoria, 2006.

[7] Shao C G. The study of indoor location algorithm based on RFID technology [D]. Beijing University of Posts and Telecommunications,2013.

[8] Wan C. Research on RFID based on indoor location algorithms [D]. Xiamen University,2014.

[9] Wan X, Liu S, Chen J X, et al. Geodesic distance-based realistic facial animation using RBF interpolation[J]. Computing in Science & Engineering, 2012, 14(5): 49-55.

[10] Weidenholzer G, Silber S, Jungmayr G, et al. A flux-based pmsm motor model using rbf interpolation for time-stepping simulations[C]//Electric Machines & Drives Conference (IEMDC), 2013 IEEE International. IEEE, 2013: 1418-1423.

[11] Wendland H. Piecewise polynomial, positive definite and compactly supported radial functions of minimal degree[J]. Advances in computational Mathematics, 1995, 4(1): 389-396.

[12] Sun J, Feng B, Xu W. Particle swarm optimization with particles having quantum behavior[C]//Congress on Evolutionary Computation. 2004.

[13] Polito S, Biondo D, Iera A, et al. Performance evaluation of active RFID location systems based on RF power measures[C]//Personal, Indoor and Mobile Radio Communications, 2007. PIMRC 2007. IEEE 18th International Symposium on. IEEE, 2007: 1-5.

[14] Seidel S Y, Rappaport T S. 914 MHz path loss prediction models for indoor wireless communications in multifloored buildings[J]. Antennas and Propagation, IEEE Transactions on, 1992, 40(2): 207-217.