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A MLE-PSO Indoor Localization Algorithm Based On RSSI

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Abstract: Received signal strength indicator (RSSI) are mostly used to measure distance in wireless sensor networks (WSNs). It is difficult to avoid the error of RSSI ranging due to the complexity of the indoor environment. However, the localization error of the existing localization algorithm will increase greatly with the increase of ranging error. In order to improve the positioning accuracy, stability as well as the dynamic perfomance of localization, a MLE-PSO indoor localization algorithm based on RSSI is proposed in this paper. This new algorithm uses an optimization algorithm the traditional particle swarm optimization (PSO) for localization, and uses a traditional localization algorithm maximum likelihood estimation (MLE) to confine initial range and the area iterative process of PSO localization process. Simulation results show that the new algorithm improves the positioning accuracy and dynamic performance effectively compared with the PSO and MLE.

Key Words: Received Signal Strength Indicator (RSSI), Indoor localization, Wireless Sensor Network (WSN), RSSI Ranging Model, Maximum Likelihood Estimation (MLE), Particle Swarm Optimization (PSO)

1 Introduction

In modern society, the rapid development of technologies such as communication, network, global positioning system (GPS) and wireless sensor networks (WSNs) make the location-aware computing and location-based services (LBS) more and more important in real life. The emergence of positioning technology greatly facilitates people's lives, and its influence has been extended to military, technology, and all aspects of people's ordinary life.

GPS is currently the most widely used and the most successful positioning technology. However, the mainstream of GPS applications are suitable outdoors, when in indoor environment GPS can not locate for the lack of GPS signals. Therefore, different kinds of indoor localization techolonigies have been developed for personal and commercial needs[1]. Now typical indoor positioning technologies are Wi-Fi technology, Bluethooth technology, infrared technology, Ultra-wide band (UWB) technology and so on. Existing wireless sensor positioning algorithm can be divided into range-based algorithm and range-free algorithm. Range-based algorithms are more widely applicated for its convenience in engineering practice. Typical ranging techniques include time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), received signal strength indicator (RSSI), and so on. Because of the short of signal propagation path indoor, the complexity of propagation environment and other issues, it is difficult to achieve accurate measured distance by TOA, TDOA or AOA, which follows the difficulty to obtain accurate location. On the contrary, RSSI is widely used because of its low cost and high precision.

The common distance-based localization methods are triangle measuring method, least squares estimation (LSE) method, maximum likelihood estimation (MLE) method, etc. But when the ranging error is large, the positioning error will be particularly large by those localizations methods. Particle Swarm Optimization (PSO) is an intelligent evolutionary computation algorithm. In the search process, the trajectory of each particle depends on the best position of particle and the best position of swarm so far. When no better individual updates the best position of swarm, all particles will quickly gather in the area of the current best position leading to premature stagnation[2].

In this paper, a new hybrid algorithm that integrates MLE and PSO is proposed for indoor localization based on RSSI. In this MLE-PSO algorithm we use MLE to confine the initial range of PSO, and to limit the area of PSO iterative process. Simulation results show that, this algorithm can greatly reduce the positioning error when ranging error change and has better dynamic performance than traditional PSO and MLE algorithms.

This paper is organized as follows. In Section 2, RSSI ranging model, MLE localization method and traditional PSO optimization algorihm are introduced and the proposed MLE-PSO algorithm is derived. The performance of the proposed algorithm is experimentally evaluated in terms of localization accuray and dynamic performance in Section 3. This paper is conclued in Section 4.

2 Localization Methods

2.1 RSSI Ranging Model

In indoor localization algorithm based on RSSI, the most commonly used wireless signal propagation model is log-normal shadowing model (LNSM)[3], which can be described as

$$RSSI_d = 10 \cdot lg(P_0) - 10 \cdot n \cdot lg(\frac{d}{d_0}) + \xi \qquad (1)$$

where $RSSI_d(dBm)$ and $P_0(dBm)$ are the received power between receiver and beacon at distance d and d_0 respectively, n is the path-loss exponent between nodes, $\xi \sim N(0, \sigma^2)$ is the noise due to log-normal shadow fading effect, where the value of standard deviation σ depends on the environmental conditions. Once we get the path-loss exponent n in the environment and the received power $RSSI_d$, then we can estimate the distance between the receiver and beacons by equation (2)

$$\tilde{d} = d_0 \cdot 10^{\frac{10lg(P_0 - RSSI_d)}{10 \cdot n}} \qquad (2)$$

where ξ is a random variable when we get the $RSSI_d$, thus there will be error between estimated distance $\tilde{d}$ and true dis-

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tance d.

In this paper, the RSSI ranging model we used is obtained from the experiments we did in an empty meeting room. We used Bluetooth Low Energy (BLE) as beacons, and smartphone as receiver. According to the iBeacon protocol proposed by Apple Inc. in 2013, the data pack that beacons send to receiver will include the received power $TXpower$ at $1m$. Therefore, we changed the model as

$$\tilde{d} = 10^{\frac{TXPower-RSSI_d}{10\cdot n}} \tag{3}$$

In our experiment environment, $n = 1.1691$, $TXPower = -58$, $\xi \sim N(0, 14.8986)$. And the distance we use in the following simulation is based on this model.

2.2 Maximum Likelihood Estimation

Suppose there are n beacons in the space, the location of ith beacon is $\vec{x_i} = [x_i \quad y_i]^T (i = 1, 2, \cdots, n)$. Denote $\vec{x} = [x \quad y]^T$ as the place of receiver, d_i as the distance between receiver and ith beacon. We can get d_i by RSSI ranging model mentioned in section 2.1. By geometric relations, we get

$$\begin{cases} (x-x_1)^2 + (y-y_1)^2 = d_1^2 \\ (x-x_2)^2 + (y-y_2)^2 = d_2^2 \\ (x-x_3)^2 + (y-y_3)^2 = d_3^2 \\ \vdots \\ (x-x_n)^2 + (y-y_n)^2 = d_n^2 \end{cases} \tag{4}$$

Subtract the nth equation from the first equation to the $(n-1)th$ equation, we have

$$\begin{cases} x_1^2 - x_n^2 + y_1^2 - y_n^2 \\ -2(x_1 - x_n)x - 2(y_1 - y_n)y = d_1^2 - d_n^2 \\ x_2^2 - x_n^2 + y_2^2 - y_n^2 \\ -2(x_2 - x_n)x - 2(y_2 - y_n)y = d_2^2 - d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 \\ -2(x_{n-1} - x_n)x - 2(y_{n-1} - y_n)y = d_{n-1}^2 - d_n^2 \end{cases} \tag{5}$$

Written in the form of linear equation $AX = b$,

where

$$A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ 2(x_2 - x_n) & 2(y_2 - y_n) \\ \vdots & \vdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{bmatrix}$$

$$b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ x_2^2 - x_n^2 + y_2^2 - y_n^2 + d_n^2 - d_2^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix}$$

$$X = \begin{bmatrix} x \\ y \end{bmatrix}$$

By maximum likelihood estimation, we obtain the solution of this equation $\hat{X} = (A^T A)^{-1} A^T b$. But there are errors between the measured distance and real diatance, so there will be large error between the position we get by MLE and the true position.

2.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an intelligent evolutionary computation algorithm proposed by James Kennedy and Russell Eberhart in 1995[4]. PSO is a powerful population-based stochastic approach to solve the nonlinear global optimization problems [5]. A group of random particles are initialized and iterate to find the optimal solution. In each iteration, the particle keeps tracking the best position of itself, known as the personal best or $pbest$ while the particle swarm also finds the best position in the whole group, called the global best or $gbest$. Each particle will change its position in the search area according to its current velocity and the distance between $pbest$ and between $gbest$. In this way the swarm is expected to move towards the optimal solution. The iteration process is as follows

$$\begin{aligned} V_i(t+1) = &\omega V_i(t) + c_1 r_1 [pbest_i(t) - x_i(t)] + \\ &c_2 r_2 [gbest(t) - x_i(t)] \end{aligned} \tag{6}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{7}$$

$$\omega = \omega_{max} - t\frac{\omega_{max} - \omega_{min}}{T} \tag{8}$$

where $V_i(t)$ is the velocity of particle i in the tth iteration, $X_i(t)$ is the positon of particle i in the tth iteration, ω is the inertia factor, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are two random constriction coeffients in the range (0,1), t is the current number of iterations, and T is the total number of iterations.

In general, PSO is used as optimization, but in this paper, we apply it as one of positioning methods by using appropriate fitness function.

Because the errors exist in the beacons and in the RSSI when we get from real environment, errors are inevitable in the positioning process. Then the essence of the localization is the minimum error, and the position estimate can be transformed into getting minimum fitness

$$f_i(\hat{X}) = d_i - |\hat{X} - X_i^T| \tag{9}$$

where d_i is the distance betwee beacon i and the receiver, X^T is the position of beacon i.

We update the swarm by PSO, optimize the fitness function in equation (10), and end the iteration process when the set precision or number of iterations is reached. Then the best particle is the estimated location.

$$fitness\hat{X} = \sum_{i=1}^{n} f_i^2(\hat{X}) \tag{10}$$

2.4 MLE-PSO Algorithm

Because of the error of distance we get between receiver and beacons, there is large error when we locate by MLE. When ulilizing PSO, we need to initialize many particles in the space and iteration multiple times which will reduce the dynamic performance of the localization algorithm, especially when the space is large.

In order to get higher accuracy as well as to get better dynamic performance, we propose a MLE-PSO positioning algorithm. The main idea of this algorithm is that we can confine the position to be located within a certain range by MLE while we can not get accurate position by MLE, then we apply PSO positioning algorithm to get the optimal estimated location. The specific process of the algorithm is as follows

Step-1 Calculate the distance between the receiver and beacons according to RSSI value by (3).

Step-2 Get the positon by MLE using the distance in step-1, and limit the initial range of PSO.

Step-3 Initialize parameters. Set the acceleration coefficients c_1 and c_2, the maximum inertia factor ω_{max} and the minimum inertia factor ω_{min}, the maximum number of iterations T, and the population of particle swarm N.

Step-4 Randomly generate particles swarm with population N within the limited range in step-2.

Step-5 Evaluate the fitness of each particle and update $pbest_i(t)$ and $gbest(t)$.

Step-6 Update the position and velocity of particle swarm according to the equations (6) (7) (8).

Step-7 Check whether the particles within the limited range, if not, pull them back within the limited range by $X_i(t+1) = X_i(t)$.

Step-8 Check whether the set precision or iteration times is reached, if yes, end iteration and output the optimal location, otherwise return to the Step-5.

And Fig. 1 presents the flow diagram of the MLE-PSO algorithm.

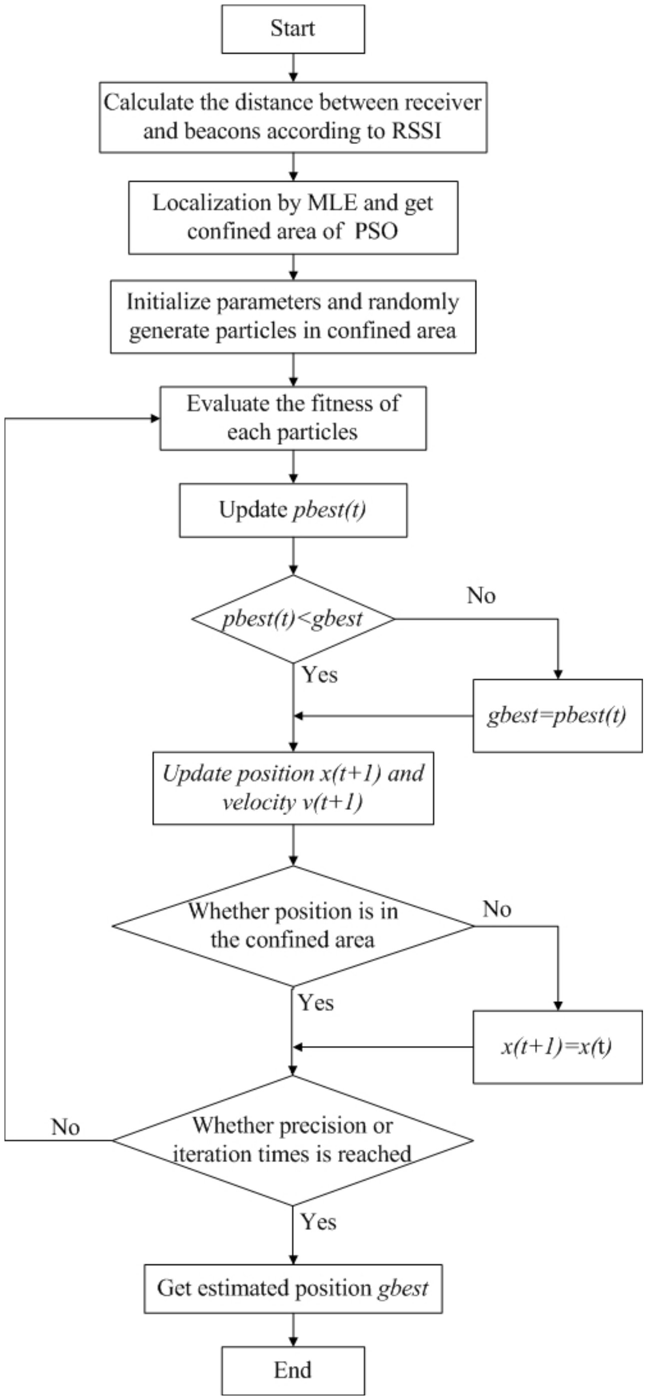

Fig. 1: Flow diagram of MLE-PSO

3 Algorithm Simulation and Analysis

3.1 Simulation Environment

In this paper, the simulation platform is MATLAB. Considering that the area of the indoor environment usually no more than $50 \times 50m$ and communication radius of beacons nowadays are usally greater than $50m$, so we assume length of the simulation space is $50m$ and the receiver can receive RSSI of all beacons. Set the number of beacon as 10, the number of position to be located as 40, the acceleration coefficients c_1 and c_2 as 2, the maximum inertia factor ω_{max} as 1 and the minimum inertia factor ω_{min} as 0.4. The positioning errors shown below are the mean error of the 40 located positions.

3.2 Positioning Error and Ranging Error

The RSSI ranging model we use is described as (3). By changing the distribution of ξ, we can change the error of ranging. Under the condition that the number of iteration is 10, the population size of particle swarm is 10, by changing ranging error, observe the change of positioning error. Repeat the simulation by 100 times, and get the mean positioning error of forty location. The result is shown in Table 1 and in Fig. 2.

From Fig. 2, with the increase of ranging error, the mean positioning errors of each positioning algorithm are all increasing. When ranging error is small (less than $3m$), MLE algorithm shows higher accuracy than PSO algorithm, but PSO algorithm shows better stability than MLE algorithm when ranging error grows. When ranging error is big, MLE algorithm can not work well.

From the results in Table 1, compared with MLE algorithm and PSO algorithm, the MLE-PSO algorithm reduces the positioning error by 50% and by 20% respectively. It is clear that with the ranging error increasing, MLE-PSO algorithm always shows better stability and higher accuracy. When ranging error is less than $3m$, localization accuracy of MLE is higher than that of PSO, so the accurateness of confined area ensure the high accurateness of MLE-PSO. When the localization caccuracy of MLE is lower than that of PSO, the confined area is larger and more inaccurate, but the localizazition process is PSO process, thus the accuracy of MLE-PSO must be higher than PSO at that time.

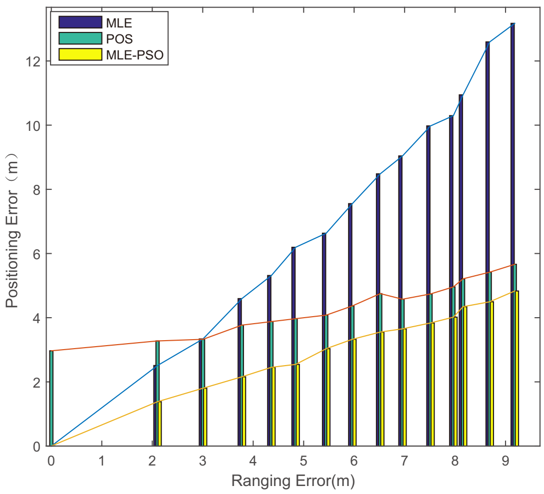

Fig. 2: Mean positioning error with ranging error increasing

Table 1: Mean positioning error with ranging error increasing

Ranging error(m)	MLE	PSO	MLE-PSO
0	0	2.97	0
2.10	2.51	3.27	1.38
3.00	3.34	3.33	1.80
3.78	4.60	3.77	2.16
4.36	5.31	3.88	2.45
4.84	6.19	3.97	2.54
5.44	6.63	4.08	3.03
5.96	7.55	4.37	3.33
6.52	8.48	4.75	3.84
6.96	9.04	4.58	3.65
7.51	9.98	4.74	3.84
7.97	10.30	4.96	4.01
8.16	10.94	5.21	4.34
8.69	12.59	5.42	4.49
9.18	13.17	5.66	4.83

3.3 Positioning Error and Number of Iterations

In order to verify the dynamic performance of the algorithms, we simulate the relationship between positioning error and number of iterations. MLE-PSO algorithm shows better stability and higher accuracy is shown in Section 3.1. So the key point of this simulation is to compare the postioning error of PSO and MLE-PSO. The result is shown in Fig. 3.

Under the condition that ranging error is about $5m$, the population size of particle sawrm is 10, repeating simulation by 100 times at each interation time, we find that with the incareasing of interation times, the accuracy of PSO and MLE-PSO localization will both increase, and the improvement of MLE-PSO is more effective than that of PSO. We come to a conclusion that the MLE-PSO has better dynamic performance than PSO algorithm when iteration time changes. But when the number is greater than 5, there is no significant improvement of standard PSO, and when the number is greater than 10, there is no significant improvement of MLE-PSO. The reason is that the fitness function of PSO and MLE-PSO is only rely on the mesured distance, we can not reduce the positioning error to 0 only by increase the number of interations. And according to the results, we can set the number of iterations as 10 for reducing computational complexity when we use those algorithms to localizate.

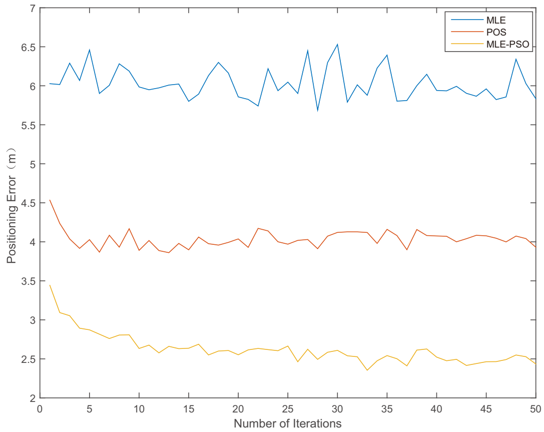

Fig. 3: Positioning error with number of interations increasing

3.4 Positioning Error and Population Size

In order to verify the dynamic performance of the algorithms, we consider another indicator, the population size of particle swarm. Changing the population size of particle swarm of PSO and MLE-PSO, results is shown in Fig. 4.

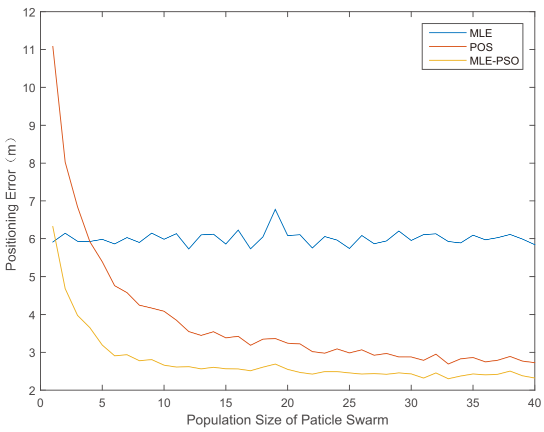

Fig. 4: Positioning error with population size increasing

The simulation conditions are that the number of iterations is 15, and the ranging error is about $5m$. From Fig. 4, when population is less than 5 the positioning errors by PSO are larger than those of MLE, but the positioning errors by MLE-PSO is less than those by MLE. With the increase of population size, the positoning accuracy of PSO and MLE-PSO is both improved. And the accuracy of PSO is approaching to that of MLE-PSO when population size is large. But when the population size increases, the dynamic performance will be reduce for the increasing in the amount of calculation. When the population size is greater than 15, there is no significant improvement of the accuracy with the increasing of population size, and at that time, the accuracy of MLE-PSO is much higher than PSO. According to the analysis above we conclude that the PSO algorithm needs more calculations to achieve same accuracy. So the MLE-PSO algorithm has better dynamic performance than PSO.

4 Conclusion

As the indoor environment is very complex, the existence of ranging error is unavoidable. A MLE-PSO indoor localization algorithm based on RSSI is proposed to improve the localization accuracy and dynamic performance in this paper. Considering that we can not receive many RSSI in the process of real positioning, firstly when we received several RSSI of beacons, we turn it to distance by ranging model, and get the estimated positon by MLE. Then, we get the confined range according to the estimated position by MLE. Finally, we initialize parameters of PSO and get the estimated location.

The proposed method is verificated on MATLAB paltform. The results show that the proposed MLE-PSO algorithm takes full advantage of the high accuracy of MLE when ranging error is small as well as the stability of PSO when ranging error is big, so the MLE-PSO algorithm exhibits higher accuracy compared with traditional MLE algorithm and PSO algorithm. At the mean time, MLE-PSO algorithm needs less times of iterations and less population of particle swarm, which shows that MLE-PSO has better dynamic performance. In the future, we will develope some localization applications and verify the effectiveness of MLE-PSO in the real environment.

References

[1] Nan Li, Jiabin Chen, Yan Yuan, A Wi-Fi Indoor Localization Strategy Using Particle Swarm Optimization Based Artificial Neural Networks, *International Journal of Distributed Sensor Networks*, Volume 2016, Article ID 4583147, 9 pages.

[2] HUO Junfei,MA Liling,YU Yuandong, Hybrid Algorithm Based Mobile Robot Localization Using DE and PSO, in *Proceedings of 32nd International Conference on Control and Automation*, Xi'an, China, July 26-28, 2013:5955–5959.

[3] BAI Si-qi, LIANG Wen-hai, Qin Shuang, Accurate Path-Loss Exponent Correcting Location Method, in *Proceedings of 33rd International Conference on Control and Automation*, Nanjing, China, July 28-30, 2014:472–475.

[4] Alan Oliveira de S, Nadia Nedjah, Luiza de Macedo Mourelle, Distributed efficient localization in swarm robotics using MinCMax and Particle Swarm Optimization, *Expert Systems With Applications*, Volume 50(2016): 55-65.

[5] Sadik Kamel Gharghan, Rosdiadee Nordin, Mahamod Ismail, A Wireless Sensor Network with Soft Computing Localization Techniques for Track Cycling Applications, *Sensors*, 2016, 16(8): 1043.

[6] S MonicaG Ferrari, A swarm-based approach to real-time 3D indoor localization: Experimental performance analysis, *Applied Soft Computing*, 2016, 43: 489-497.

[7] C AnagnostopoulosS HadjiefthymiadesK Kolomvatsos, Accurate, Dynamic, and Distributed Localization of Phenomena for Mobile Sensor Networks, *Acm Transactions on Sensor Networks*, 2016, 12(2): 1-59.

[8] NI Hu-Shengj,XU Wu-Jun,LI Yuan-Yuan, An Improved Method of Self-Adaptive Localization for Wireless Sensor Network in Dynamic Indoor Enviroment, in *Proceedings of 31st International Conference on Control and Automation*, Hefei, China, July 25-27, 2012:6574–6577.

[9] GAO Yun-guang, WANG Shi-cheng, LIU Zhi-guo, An Intelligent Fault Tolerant Filter Algorithm Based on RBF Neural Network Optimized by Genetic Algorithm, *Journal of Astronautics*, Vol.32, No.8, August 2011: 1715-1721.

[10] FANG Wangsheng, LIU Xiaoxin, Research of RSSI algorithm based on rank of matrix and chaos particle swarm optimization algorithm. *Computer Engineering and Applications*, 2016, 52 (4): 74-78.

[11] XING Ming-yanLI La-yuan, Application of particle swarm optimization to positioning for wireless sensor networks. *Computer Engineering and Applications*, 2009, 45 (32): 72-74.

[12] CHEN Xing-zhou, LIAO Ming-hong, LIN Jian-hua, Improvement of node localization in wireless sensor network based on particle swarm optimization. *Journal of Computer Applications*, Vol.30, No.7, July 2010: 1736-1738.