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A NOVEL HYBRID LOCALIZATION METHOD FOR WIRELESS SENSOR NETWORK

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Abstract- Wireless sensor network is a kind of brand-new information acquisition platform, which is realized by the introduction of self-organizing and auto-configuration mechanisms. Node localization technology represents a crucial component of wireless sensor network. In this paper, a localization method based on kernel principal component analysis and particle swarm optimization back propagation algorithm is carefully discussed. First of all, taking KPCA as the front-end system to extract the main components of the localization information, and then regarding the nonlinear principal components extracted from distance vectors as the input samples, and meanwhile taking the coordinates of vertices in addition to the region boundary as the output samples, the PSO-BP neural network is trained to achieve the localization model. Finally the localization of unknown nodes can be estimated. The simulation experiment result showed that the method has high ability of stability and precision, and meets the practical need of localization.

Index terms: Wireless sensor network, localization, kernel principal component analysis, particle swarm optimization, back-propagation algorithm.

I. INTRODUCTION

Wireless sensor network (WSN) is a kind of brand new information acquisition platform, which is realized by the introduction of self-organizing and auto-configuration mechanisms [1,2]. It is expected to offer a convenient solution not only for complex monitoring and control applications, but also for more advanced applications such as localization services [3]. Node localization technology currently represents a crucial component of wireless sensor network. Localization estimation can be very useful for many applications such as tracking the traces of objects, indoor guiding of persons in complex buildings, security, tour guides[4-6].

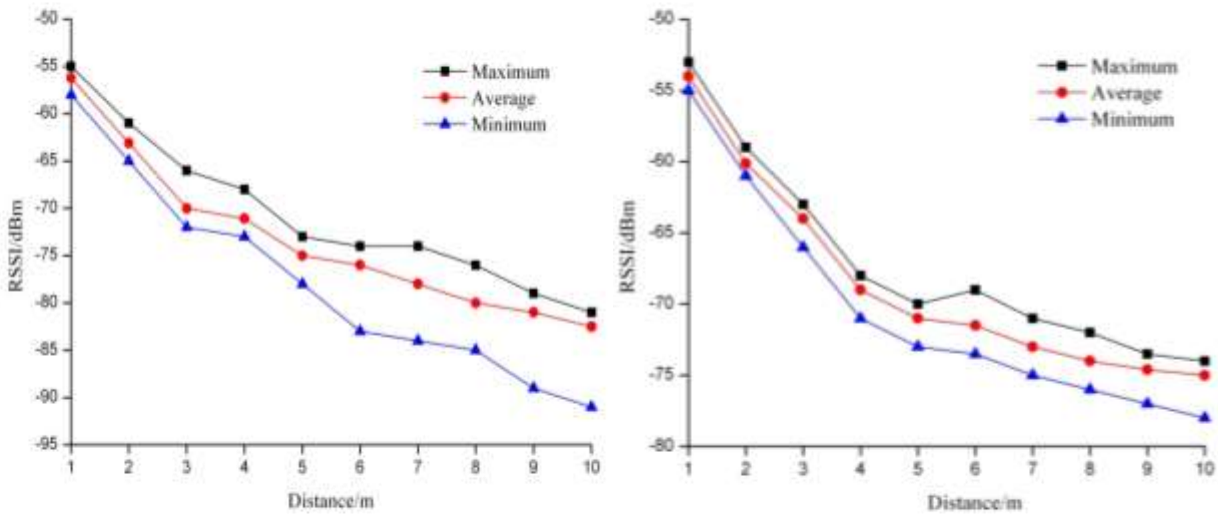
Although global positioning system (GPS) is a popular localization estimation system, it is ineffective indoors, in cities with tall buildings, or between mountains due to the requirement of line-of-sight (LoS) for the communication with the satellites. Thus, there is a need for accurate indoor localization technology. Using wireless sensor network instead of GPS makes indoor localization possible. Over the years, many researchers have proposed many different methods for this problem[7-9]. There are two kinds of localization algorithms: range-based algorithm and range-free algorithm. Range-based algorithm requires accurate distance or angle measurements to obtain node localization, with commonly relying on extra hardware other than radio transceiver. Range-based algorithm includes RSSI (Received Signal Strength Indicators), TOA(Time of arrival), TDOA(Time difference of arrival), AOA(Angle of arrival), and so on[10-12]. Range-free algorithm localizes nodes through network connectivity, but with low accuracy. Among the methods, the distance measuring method based on RSSI measures signal strength by applying wireless transceiver chip. Without any additional devices, the distance measuring method has low cost and low energy consumption and easy to be achieved. It has become a chief method in wireless sensor network localization.

Principal component analysis (PCA) is one of the most commonly used feature extraction method, which can achieve good effect in the process of linear problem. However, PCA has some limitations for complicated localization data. Kernel principal component analysis (KPCA) is a new kind of nonlinear multivariate statistical analysis method for PCA, by using of kernel optimization. Due to the application of kernel technique, KPCA has many advantages over PCA, especially in extracting nonlinear features [13]. It provides an effective method for localization data feature extraction for reducing data dimension and increasing localization accuracy. A hybrid algorithm combining particle swarm optimization(PSO) algorithm with back-propagation (BP) algorithm, is a kind of modern heuristic and random search algorithm based on optimization model of autonomous animals, with the advantages of insensitiveness in initial value, strong robustness, simplicity and easy realization[14, 15]. Currently, the hybrid algorithm is applied in RSSI localization by wireless sensor network.

In order to solve the problems mentioned above, this paper proposed a kind of wireless sensor network localization method by integrating KPCA and PSO-BP. First, through the nonlinear feature extraction method based on KPCA, the original localization data can be mapped to a high-dimensional feature space. Secondly, new localization characteristic information is extracted by transforming, availably reducing the noise and redundancy of the original localization. Afterwards, the nonlinear relationship between the localization information and the unknown node coordinates is modeled based on the PSO-BP algorithm, and finally, the localization of unknown nodes can be estimated by the model.

II. RSSI CHARACTERISTIC AND DISTANCE ESTIMATION

In order to obtain the RSSI characteristic of wireless signal propagating in real space, the indoor and outdoor wireless communication tests are carried out. The test conditions were: transmit power 3 dBm; whip omni-directional antenna gain 3 dBi; antenna height 0.3 m. In different environment of every different distance, RSSI value of the receiver was measured at 50 times. According to that, RSSI change curves were draw. As can be seen from Figure 1, the RSSI value and the transmission distance are in the trend of nonlinear attenuation, and there is a certain level of jitter. The closer the transmission distance is, the faster the attenuation of the power becomes. And the farther the transmission distance is, the slower the attenuation of the power becomes. (In other words, the corresponding relation between the transmission distance and RSSI is better, and vice versa).



(a) Indoor (b) Outdoor

Figure 1. RSSI change curves in different environment.

RSSI distance estimation method estimates distance based on received signal strength or path loss model in theory or experiences, with its statistical model as follows[16].

$$\overline{P_r(d)} = P_r(d_0) - 10\beta\log(\frac{d}{d_0}) \qquad (1)$$

In Equation (1)， d_0 is reference distance, m; d is the distance between the receiving terminal and the transmitting terminal, m; $\overline{P_r(d)}$ is the average power in receiving signals when the distance is d, dBm; $P_r(d_0)$ is the power when the reference distance is at d_0, dBm; β is the path loss index, indicating the rate of path loss with distance increasing.

In distance estimation, the signal strength is expressed by

$$RSSI = P_t + G - \overline{P_L(d)} = \overline{P_r(d)} \qquad (2)$$

In this equation, $\overline{P_r(d)}$ is the received signal strength after passing the distance d, i.e. RSSI, dBm; P_t is the power of transmitting signals, dBm; G is the antenna gain, dBi; $\overline{P_L(d)}$ is the average path loss when the transmitting distance is d, dB.

III. LOCALIZATION NETWORK MODEL

As is shown in Figure 2, the localization model schematic diagram, wireless sensor nodes $S = \{S_i | i = 1,2,\cdots,M\}$ are randomly placed within a three-dimensional cube area $(a \times b \times c)$. Each node has the same construction and the same computing capability. All nodes are divided into beacon nodes and unknown nodes according to their functions. The localization of first *n* nodes $S_1(x_1, y_1), S_2(x_2, y_2), \cdots, S_n(x_n, y_n)$ can be obtained in advance by peripheral equipment such as GPS or the real distribution as the beacon nodes; the nodes $S_i(x_i, y_i)(n < i \leq M)$ have no specific hardware equipment to obtain their information as unknown nodes. For the generality of the problem, the following items are supposed in this paper:

1. The unknown nodes can move freely in this area;
2. The time of all sensor nodes are strictly synchronous and can communicate each other directly.

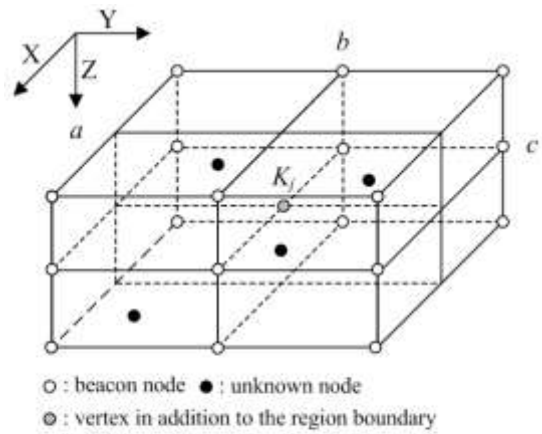


Figure 2. Schematic diagram of network model

After the completion of the network deployment, a beacon node is randomly selected as the sink node; then the beacon node divides the cube area through the virtual grids ($\frac{a}{N} \times \frac{b}{N} \times \frac{c}{N}$, *N* indicates the total number of virtual grids), and the vertices in addition to the region boundary are expressed as K_j (j=1,2,⋯,$(N-1)^3$). At last, the actual distance between the beacon nodes and the unknown nodes is d_i ($1 \leqslant i \leqslant n$, *n* indicates the total number of beacon nodes), and d_i can form a distance vector $T = [d_1, d_2, \cdots, d_n]$. It can be proved that there was a nonlinear mapping relationship between the unknown node coordinates and the distance vector *T*.

In the process of localization, by mutual communication between beacon nodes, the network topology graph and data link list are established in the sink node; then the sink node divides the cube localization area through the virtual grids, and obtain the theoretical distances between beacon nodes and the vertices in addition to the region boundary to compose corresponding distance vector. Taking KPCA as the front-end system, and the main components of the localization information are extracted by eliminating the relativity. Finally, regarding the nonlinear principal components extracted from distance vectors as the input samples, meanwhile, taking the coordinates of vertices in addition to the region boundary as the output samples, the PSO-BP neural network is trained to gain the localization model, and the localization of unknown nodes can be estimated. Localization algorithm flow chart is shown in Figure 3.

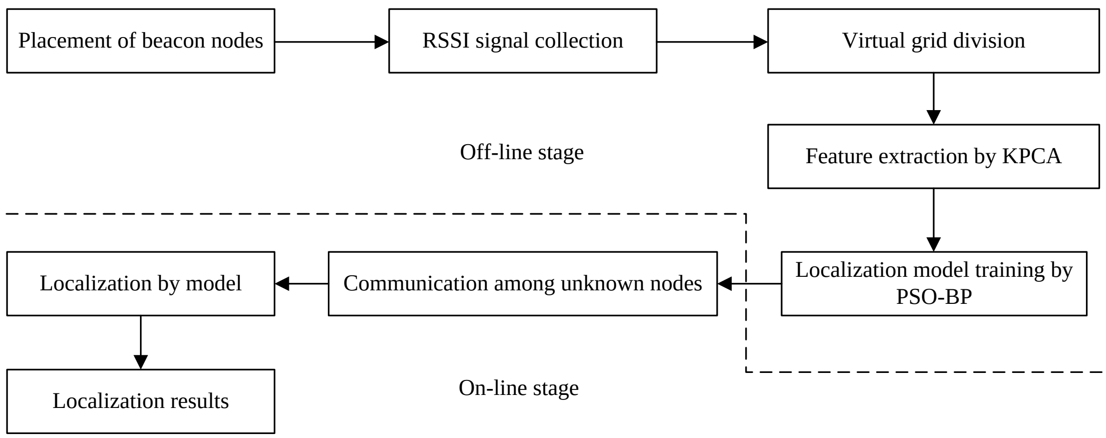


Figure 3. Localization algorithm flow chart.

IV. KPCA FEATURE EXTRACTION

PCA can project the linear data matrix onto an uncorrelated subspace, which achieves the purpose of dimensionality reduction and keeps important information simultaneously [17,18]. However, the characteristics of real industrial data are complex, such as nonlinearity, dynamic, and non-Gaussians, which lead to weak PCA performance. KPCA algorithms have been proposed to solve such problems [19,20]. KPCA transforms original data from data space to feature space by nonlinear mapping, and the optimal projection direction is obtained by using the PCA algorithm in the feature space. Afterwards, the nonlinear characteristic of original data is determined. The relevant algorithm process is as follows.

x_i $(i = 1,2,\cdots,N)$ was N sample point for q dimensional input space; $\varphi(x_i)$ $(i = 1,2,\cdots,N)$ was the sample point corresponding to feature space F.

Principal component analysis was achieved by solving the eigenvalues and eigenvectors of sample covariance matrix in the feature space F. The covariance matrix of the feature space is computed as in Equation (3).

$$C_\varphi = \frac{1}{N}\sum_{i=1}^{N}\varphi(x_i)\varphi(x_i)^T \qquad (3)$$

The eigenvalues and eigenvectors of C_φ can be calculated by

$$C_\varphi \nu = \lambda \nu \qquad (4)$$

where λ and ν represent matrix eigenvalues and corresponding eigenvectors.

The covariance matrix is symmetric, which can find the r standard orthogonal feature vector, namely Equation (4) has the same number of non-zero solutions. But because the transform is unknown, matrix C_φ cannot be obtained, and therefore cannot directly solve the feature vector ν. According to the theory of reproducing kernel, the feature vector ν can be determined by the samples in space F, and expressed by

$$\nu = \sum_{j=1}^{N} a_j \varphi(x_j) \qquad (5)$$

$$\varphi(x) \bullet C_\varphi \nu = \lambda(\varphi(x) \bullet \nu) \qquad (6)$$

Substituting Equation (4) and Equation (5) into Equation (6), Equation (7) can be obtained.

$$Ka = n\lambda a \qquad (7)$$

where $K_{N\times N} = (\varphi(x_i)\bullet\varphi(x_j))\ (i, j = 1,2,\cdots,N)$ is kernel matrix. The kernel matrix K needs to be formed by the inner product of the vectors in high dimensional feature space, which can be defined by the kernel function in the support vector machine technology. By choosing the appropriate kernel function, the eigenvalues and eigenvectors of the kernel matrix can be solved, and then the principal vector of the feature space is obtained by PCA.

V. LOCALIZATION ALGORITHM BASED ON PSO-BP NEURAL NETWORK

BP network is a multilayer feed-forward network trained by the error back propagation algorithm [21,22]. The input data passes from the input layer nodes to the hidden nodes followed by the transfer function, then spread to the output nodes. BP network is approximate to complex function after a number of simple nonlinear functions, and it can obtain the output data using input data at will. BP network is suitable for establishing the nonlinear relationship between the location information of KPCA extraction and the unknown node coordinates, but it is easy to fall into local minimum, slow convergence rate and poor generalization ability. Particle swarm optimization algorithm based on swarm intelligence does not require with the characteristics information of the problem itself, and can effectively shorten the training time of neural network, so using the PSO algorithm to optimize the BP network to find the optimal weights and thresholds of the network before training[23,24]. Particle velocity and position update rule are expressed as follows.

$$v_{id}(t+1) = w \cdot v_{id}(t) + c_1 rand()(p_{id}(t) - x_{id}(t)) + c_2 rand()(p_{gd}(t) - x_{id}(t)) \quad (8)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (9)$$

In Equation (8) and Equation (9), $v_{id}(t+1)$ indicates the speed of the i^{th} particle in the $(t+1)^{th}$ iteration in the d^{th} dimension, $P_{id}(t)$ is the individual optimal solution of the i^{th} particle in the t^{th} iteration, $P_{gd}(t)$ is the optimal solution of the whole particle swarm optimization in the t^{th} iteration, x_{id} represents the d^{th} dimension of the i^{th} particle, c_1 and c_2 are acceleration constants, *rand*( ) indicates the random number of 0 to 1. w is the inertia weight, and its expression can be described by

$$w = w_{\max} - (w_{\max} - w_{\min})\frac{t}{M} \quad (10)$$

where $w_{\max}$ is the maximum value of inertia weights, $w_{\min}$ is the minimum value of inertia weights, t is the current iteration number, and M is the maximum iteration number.

The algorithm process of PSO-BP neural network model is as follows:

Step 1: According to the training sample, the number of input nodes is r, the number of output nodes is s, and the number of hidden layer nodes is p. d is the sum of the weights and thresholds in BP network, and can be obtained by

$$d = r \times p + p + p \times s + s \quad (11)$$

Step 2: The inertia weights and acceleration constants are initialized respectively. The parameters such as the particle swarm size R and the maximum number of iteration M are given.

Step 3: The fitness of the particles are calculated, namely the actual output results of all samples in accordance with the direction of the BP network are obtained for each particle.

Step 4: The current fitness value and the fitness value of the best position P_{id} it has experienced are compared for each particle, if better, then P_{id} is updated. The current fitness value and the fitness value of the best swarm position P_{gd} are compared for each particle, if better, then P_{gd} is updated.

Step 5: According to Equation (8) and Equation (9), the speed and position of each particle are updated.

Step 6: If the algorithm meets the convergence criterion or the maximum number of iterations, the PSO algorithm is exited, and the Step 7 is implemented, otherwise Step 3 is carried out.

Step 7: Using the BP algorithm to train the neural network, the optimal training results are exported.

VI. EXPERIMENTAL RESULTS AND ANALYSIS

In order to test the function of the algorithm, we establish a experiment platform to test the wireless sensor network localization system, and the experiment model is shown in Figure 4. The experiment is set as follows:

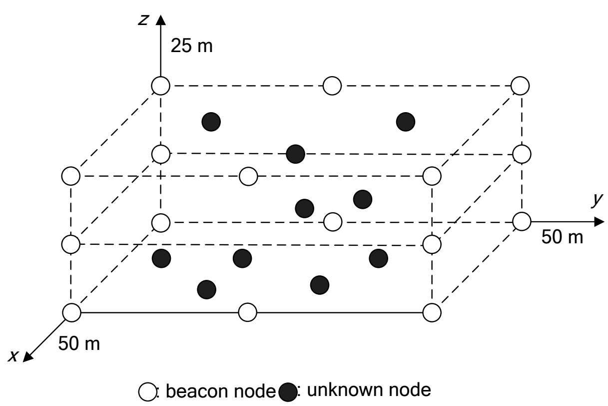


Figure 4. Experiment model

1. The three-dimensional area is 50 m×50 m×20 m;
2. The total number of bean nodes is 16;
3. Ten points are randomly selected as the unknown nodes to carry on the test in the localization region;
4. The signal emission power of beacon nodes P_t is 30 dBm, with the reference distance d_0 of 20 m, the transmitting antenna gain G_t and the receiving antenna gain G_r are both 1 dBi, with path loss index β as 2;

5. In order to describe the impact of real environment on RSSI distance estimation, the corresponding signal transmitting strength is calculated according to node distribution, and on this basis, Gaussian random variable λ is added as the environmental interference;
6. The localization result is the average value of 100 simulation times under the same parameters. Localization error is defined by

$$RMSE = \sqrt{(x-\hat{x})^2 + (y-\hat{y})^2 + (z-\hat{z})^2} \tag{12}$$

where (x, y, z) is the real localization and $(\hat{x}, \hat{y}, \hat{z})$ is the estimated localization.

Beacon nodes use wireless communication module SZ02 produced by Shunzhou Tecnology Co.,Ltd. Wireless communication module SZ02 is an enhanced module ZIGBEE, which integrates RF receive and microprocessor in accordance with ZIGBEE protocol standard. It has the advantages of far communication distance, strong anti-interference ability, flexible network and other outstanding advantages and characteristics. It can be composed of star type and MESH type and other complex net network structures.Unknown nodes use the wireless communication module based on MC13213 chip produced by Freescale.The MC1321x series is the secondary ZigBee development platform of Freescale.It can be used to connect simple and dedicated point-to-point connection with a complete ZigBee mesh network. Practicality pictures of beacon node and unknown node are shown in Figure 5.

(a) (b)

Figure 5. Picture of beacon node (a) and unknown node (b)

First the localization area is divided by the virtual grid (5 m×5 m×2.5 m), the number of the vertices in addition to the region boundary is 729, and the number of distance vector dimension is 16. Polynomial kernel function is chosen as kernel function, which can be defined by

$$k(x, x') = [(x, x') + 1]^2 \tag{13}$$

The eigenvalues of the kernel matrix K are sorted in descending order ($\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$). The principal component number is chosen according to Equation (14).

$$\left(\sum_{k=1}^{m} \lambda_k \Big/ \sum_{i=1}^{n} \lambda_i \right) \geq E \tag{14}$$

where E is the cumulative contribution rate. E is equal or greater than 0.96 to ensure that the KPCA feature extraction can contain more information on the localization feature. KPCA method is applied to extract the feature of all distance vector and rank the eigenvalues. The results are shown in Table 1, and the cumulative contribution rate of the first 4 principal components has been reached 97.76%. namely the required number of principal components is determined as 4.

Table 1: Analysis Results of KPCA

Serial Number of Eigenvalues	λ_k	Contribution Rate	Cumulative Contribution Rate
1	9.0529	0.5658	0.5658
2	5.6271	0.3517	0.9175
3	0.5351	0.0334	0.9509
4	0.4272	0.0267	0.9776
5	0.2464	0.0154	0.9930
6	0.0428	0.0027	0.9957

KPCA method is compared with PCA, the cumulative contribution rate of the principal components is respectively showed in Figure 6. It can be observed that KPCA has better feature extraction effect and excellent analysis ability.

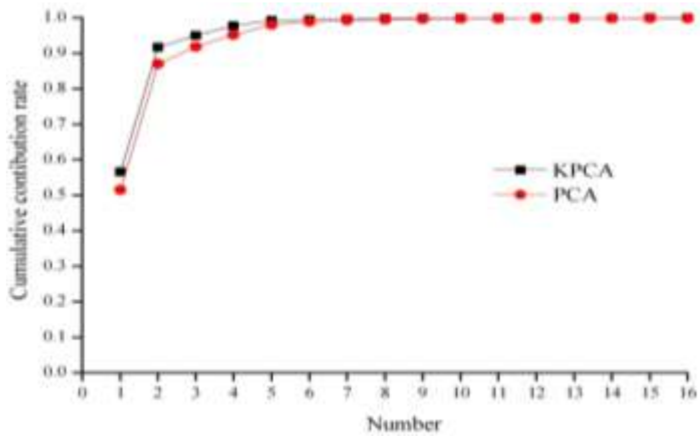


Figure 6. Comparison of performance of feature extraction

Then taking the extracted feature vectors as the input sample, taking the coordinates of vertices in addition to the region boundary as the output samples, the training data set of PSO-BP neural network is established. According to the feature of training data set and the Kolmogorov theorem, the number of input nodes is 4, the number of output nodes is 3, and the number of the hidden layer node is 10. The transfer function of the hidden layer neurons as tansig, and the transfer function of the output layer neurons is chosen as logsig. Optimal maximum iteration number M helps to shorten the algorithm running time and improve the localization efficiency. Too large M value often reduces the real-time performance of the algorithm. Selecting different maximum iteration number to test, localization result is shown in Figure 7, It can be seen that when the M ranges from 50 to 200, the average localization error decreases along with the increasing of M; and when M ranges from 200 to 500, the average localization error is basically constant. Therefore, the maximum iteration number of the algorithm (M) is 200.

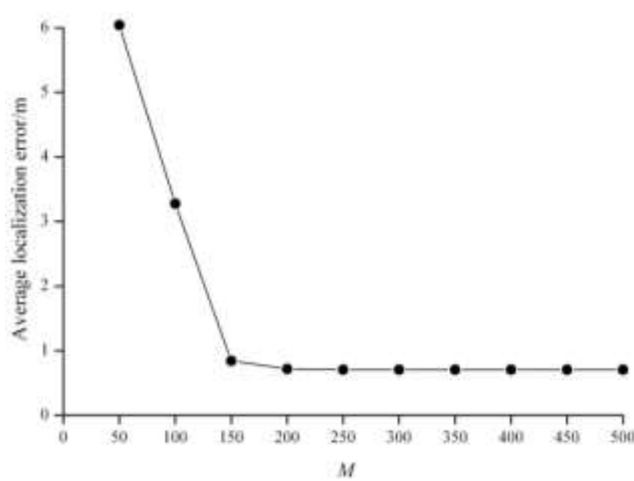


Figure 7. Effect of maximum iteration number M on average localization error

The training processes of PSO-BP neural network and genetic BP neural network are compared, and the changes of fitness values are shown in Figure 8. It can be observed that the fitness value of PSO-BP neural network is decreased rapidly and the optimal fitness value is reached by 25 times. The whole training process shows that the particle swarm optimization algorithm has good effect, and can find the optimal weights and thresholds of BP neural network with a small cost.

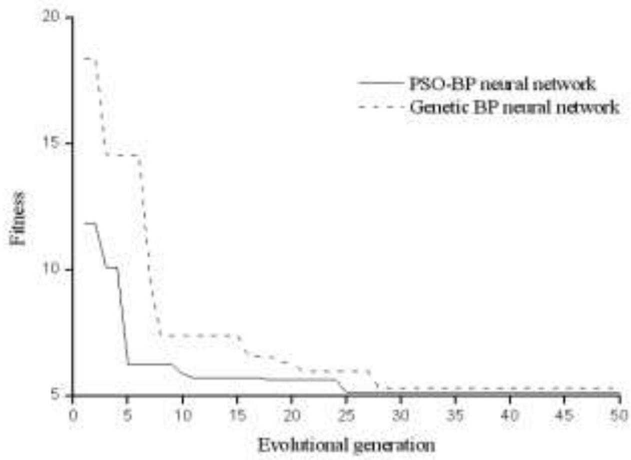


Figure 8. Evolution of fitness curve of

Finally, 10 samples corresponding to the unknown nodes are served as test samples to study the localization model. The localization errors of the PSO-BP neural network model are compared with the localization errors of genetic BP neural network model and support vector machine model, and the localization results shown in Figure 9. The average localization errors of three algorithms are 0.288689 m, 1.136445 m and 1.36062 m respectively, indicating that the algorithm proposed in this paper is better in performances, and it shows that the localization algorithm proposed in this paper can meet the demands of most wireless sensor network application research.

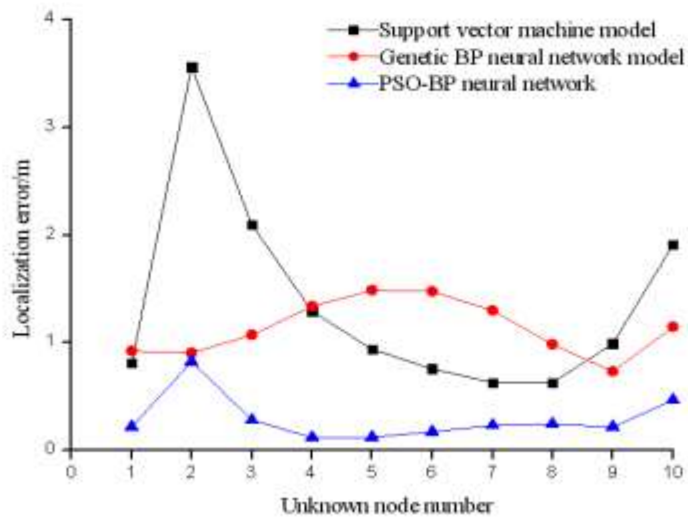


Figure 9. Comparison of localization performance

The experiment result showed that the stability and localization accuracy of the method are better than the genetic BP neural network model and support vector machine model. Under the condition of same measure error and the equal number of anchor nodes, the method was compared with the genetic BP neural network model and support vector machine model. The maximum of localization error was 0.8062 m, 1.4765 m and 3.5553 m respectively, the minimum of localization error was 0.1298 m, 0.7398 m and 0.6440 m respectively, and the average localization error was 0.288689 m, 1.136445 m and 1.36062 m respectively. The curve of PSO-BP neural network is smoother than the other two, and the experiment result indicates that the method is actable and the precision is well. It is very suitable for wireless sensor network localization.

The localization nodes will be attacked maliciously or interfered by complex elements in localization environment. Thus different Gaussian random variables are added for the localization test, with the localization results shown in Figure 10. It can be observed that with the increase of standard deviation of the Gaussian random variables, the localization errors have the increasing tendency. When the Gaussian random variables are N(0, 15), N(0, 20) and N(0, 25), the average localization errors are N(0, 15), N(0, 20) and N(0, 35) respectively. The largest localization error is 4.17% of the diagonal line distance of the testing three-dimensional area. It shows that, the localization algorithm proposed in this paper is not sensitive to errors in distance estimation with strong robustness. And its accuracy in localization can meet the demands of most wireless sensor network application research.

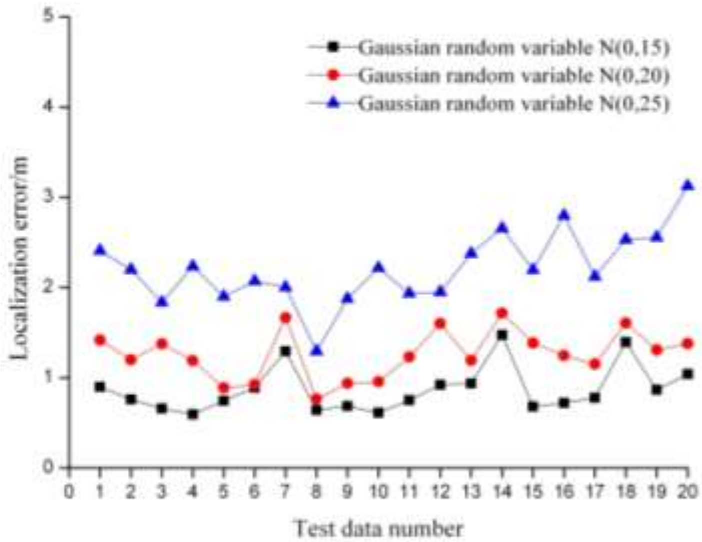


Figure 10. Effect of Gaussian random variable on localization errors

VII. CONCLUSIONS

Wireless sensor network (WSN) has attracted significant attention over the past few years. A growing list of civil and military applications can employ WSN for increased effectiveness; especially in hostile and remote areas. Examples include disaster management, border protection, combat field surveillance.

In this paper, a kind of wireless sensor network localization method is proposed by integrating KPCA and PSO-BP. The main components of the localization information are extracted by KPCA. By taking the nonlinear principal components extracted from distance vectors as the input samples, applying the coordinates of vertices in addition to the region boundary as the output samples, the PSO-BP neural network is trained to gain the localization model, and meanwhile the localization of unknown nodes can be estimated. Through simulation testing analysis on the performances in node localization, the algorithm has certain significance in wireless sensor network localization with the advantage of finding out the optimized solution and maintain the average localization error on an ideal level. The following conclusions can be drawn:

1. This algorithm can effectively overcome the negative impacts high-dimension information on localization, and by reasonably selecting the key feature vectors which are sensitive to localization results, the localization accuracy was effectively raised. The algorithm has certain significance in wireless sensor network localization.

2. The nonlinear feature extraction method based on KPCA can effectively extract the main components of the localization information, and eliminate data correlation to reduce the dimensions of the sample space.
3. PSO algorithm is applied to improve the BP neural network. The simulation results show that the PSO algorithm can effectively overcome the defects of the BP neural network.

VII. ACKNOWLEDGEMENTS

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