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Three-dimensional Sensor Node Localization based on AFSA-LSSVM

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Abstract

In order to improve location precision of three-dimensional sensor nodes, a novel three dimensional node location method of wireless sensor network is proposed in this paper based on least squares support vector machine (LSSVM) which parameters are optimized by artificial fish algorithm (AFSA). Firstly, the study samples are constructed for three-dimensional nodes localization model, and then LSSVM is used to build three-dimensional node localization model in which fish foraging behavior, cluster are simulated to find the optimal parameters of LSSVM, and finally the performance is tested by simulation experiment. The results show that, compared with other localization method, the proposed method can improve the precision of the sensor nodes and it has some practical application values.

Keywords: *Wireless Sensor Network; Three-dimensional node Localization; LSSVM; artificial fish swarm algorithm*

1. Introduction

Node positioning technology is a key technology in wireless sensor network (Wireless Sensor Network, WSN). Currently, two-dimensional WSN node positioning technology is relatively mature, but with the expanding range of applications, the distribution of nodes develops from the two-dimensional spatial distribution to the environment of three-dimensional space, such as forests, oceans, etc. As it is hard for the two-dimensional method to meet the requirements of three-dimensional sensor node positioning, the improvement of the node accuracy of three-dimensional sensors has become a hot topic in the research on WSN [1, 2].

For the node positioning of three-dimensional WSN, many domestic and foreign experts and scholars have made a lot of research, and presented many node positioning algorithms [3]. Liu Chong et al put forward a three-dimensional WSN node positioning method based on APIS. The method does not require ranging, simple and easy to implement, but the positioning accuracy is closely related to the beacon nodes, so its robustness is poor [4]. Wang Quandi *et al.*, put forward a three-dimensional node positioning method based on multidimensional scaling (MDS), which requires multiple iterations and high computational complexity. By using this method, it is difficult to meet the requirements of real-time sensor node positioning [5]. Jiang Peng *et al.*, proposed a method for three-dimensional node self-positioning by combining AOA and concentric positioning together, and achieved good effects, but due to the complex implementation, its range of applications is limited [6]. Jiang Yusheng et al proposed a positioning method based on DV-Hop which does not need ranging technology. The method does not require additional hardware and is at low cost, but adversely affected by the accumulated error, its positioning results are not satisfactory [7]. In recent years, with the development of swarm intelligence algorithms and machine learning, Jiang Yusheng utilized the global optimization capability of genetic algorithm and applied it in the process of indoor three-dimensional positioning, but it is more sensitive to noise with poor anti-interference ability [8]. Guo Xiaolei utilized

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the powerful nonlinear approaching capacity of BP neural network, to use it in the three-dimensional sensor node positioning. Though it improves the positioning accuracy, there are deficiencies such as the difficulty of BP neural network in determining the network structure, and easy occurrence of over-fitting, *etc.*, [9]. Zhou Songbin et al put forward the WSN node positioning method based on Least Squares Support Vector Machine Classifier (LSSVM). LSSVM better overcomes the shortcomings of neural network, such as over-fitting and slow training of standard SVM, which provides a new research tool for WSN node positioning [10]. However, in the practical application of LSSVM, the node positioning performance and parameters are directly related, so to obtain high positioning accuracy of the three-dimensional sensor, we must first select the most adaptable LSSVM parameters [11].

Artificial Fish Swarm Algorithm (AFSA) is an intelligence algorithm through simulation of foraging behavior of fish swarms, with the advantages of strong robustness and easy implementation, etc, which has achieved good application effect in the field of combinatorial optimization. [12] The parameter selection of LSSVM is actually the combinatorial optimization problem of large-scale space search, so it can be solved by means of AFSA. With regard to this, a three-dimensional AFSA optimized LSSVM WSN node positioning method (AFSA-LSSVM) is proposed and through simulation experiment, the effectiveness of AFSA-LSSVM has been verified.

2. Three-dimensional LSSVM WSN Node Positioning Method

2.1. Packet Broadcast Stage of Beacon Node

The beacon node broadcasts data packet with its own information to WSN, and after th e node receives the message, one hop value is added. Broadcast of other sensor nodes cont inues until the entire network is covered [13].

2.2. Calculation of the Distance of each Hop

According to the position information and the number of hops of other beacon nodes, the average network hop distance of each beacon node is estimated by using formula (1):

$$HopSize_i = \frac{\sum_{j \neq i} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{j \neq i} hopS_{ij}} \quad (1)$$

Where, j is the number of another node in the data table of beacon node i, and $hopS_{ij}$ is the hops between nodes i and j.

After a beacon node broadcasts the average hop distance to the whole network, the unknown node only records the first average hop distance, and forwards it to neighbor nodes. After receiving the average hop distance, according to the hop count information recorded, the unknown node estimates the distance from unknown node i to some beacon node by using formula (2):

$$L_i = S_i \times HopSize \quad (2)$$

2.3. LSSVM Modeling and Positioning of the Nodes

(1) Assuming the distance from the node to be positioned $S_l'(x_l', y_l', z_l')$, $(l = 1, 2, \dots, M)$ to the beacon node S_j ($j \in 1,2,\dots, M$) is d_{ij}', the distance vector between S_l' and each beacon node will be $R_l' = [d_{i1}', d_{i2}',\dots, d_{iL}']$. The distance vector R_l' of nodes to be positioned, the number of which is M and its coordinates (x_l', y_l') are collected to

form the training sample set $U_X = \{(R'_l, x'_l) | l = 1,2,..., M\}$, $U_Y = \{(R'_l, y'_l) | l = 1,2,..., M\}$ and $U_z = \{(R'_l, z'_l) | l = 1,2,..., M\}$.

(2) LSSVM is used to train the sample sets U_X, U_Y, U_Z, respectively, to constitute U_X and solve the optimization problem, as shown in formula (3).

$$\begin{aligned} &\min_{\omega,\xi,b} \frac{1}{2}\|\omega\|^2 + \gamma \frac{1}{2}\sum_{i=1}^{M} \xi^2 \\ &s.t. \\ &x'_l = \omega^T \phi(R'_l) + b + \xi_l \\ &l = 1, 2, \ldots, M \end{aligned} \tag{3}$$

Where, φ (i) is a nonlinear mapping function; ω is the *weight;* γ is the regularization parameter*;* ξ_i is a random error [14].

There are currently many kernel functions of LSSVM, and the advantages of its radial basis function are parameters and versatility, *etc*. In this paper, the radial basis is selected as LSSVM kernel function, specifically defined as:

$$\begin{aligned} &K(R'_m, R'_n) = \exp\left(\frac{-\|R'_m, R'_n\|^2}{2\sigma^2}\right) \\ &(m, n = 1, 2, \ldots, M) \end{aligned} \tag{4}$$

By introducing Lagrange operators a and b, the formula (3) is transformed into the dual problem, namely

$$\begin{bmatrix} 0 & \bar{1}^T \\ \bar{1} & \Omega + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ x' \end{bmatrix} \tag{5}$$

In the formula, $x' = [x'_1, x'_2, ..., x'_M]^T$, $a = [a_1, a_2, ..., a_M]^T$, $\bar{1} = [1,1,...,1]^T$, $\Omega(m, n) = K(R'_m, R'_n)$.

Through $\begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 & \bar{1}^T \\ \bar{1} & \Omega + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} o \\ x' \end{bmatrix}$, a and b can be obtained, and the decision function of LSSVM obtained is

$$\hat{x} = f_x(R) = \sum_{l=1}^{M} a_i K(R_i, R'_i) + b \tag{6}$$

(4) The distance from unknown node S i to each beacon node is d ij, which constitutes the distance vector Ri=[di1,di2,…,diL], as the input vector of decision functions fx, fy, fz. $\hat{x}_i$, $\hat{y}_i$, $\hat{z}_i$ are obtained, that is, ($\hat{x}_i, \hat{y}_i, \hat{z}_i$) is the estimated coordinate value of the unknown node Si.

3. AFSA-LSSVM

It can be seen from the LSSVM modeling process, RBF kernel function σ and regularization parameter γ values have greater impacts on the performance of LSSVM. The grid search algorithm, genetic algorithm and particle swarm algorithm frequently used to solve the parameters now are time-consuming and tend to get local optimal solutions. Given the competitive global search capability of AFSA and its advantages of simple and easy implementation, AFSA is used in this paper to search and find the optimal LSSVM parameter, s o as to improve the accuracy of the sensor node positioning.

3.1. AFSA

Artificial Fish Swarm Algorithm (AFSA) is a swarm intelligence algorithm by imitating the foraging and rear-ending of fish swarms. There are several typical behaviors as follows:

(1) Foraging behavior. Let the current position of the artificial fish be X_i, and randomly select a location X_j. If the food density at X_i is not less than X_j, move forward by one step in this direction, or, make the random selection of location X_j for another time and still randomly, and then make a judgment; if the forward condition can not be reached after n_j times of trials, make a step forward randomly.

$$\begin{cases} X_{i|next} = X_i + Rand() \cdot Step \cdot \dfrac{X_j - X_i}{\left\| X_j - X_i \right\|} & Y_i < Y_j \\ X_{i|next} = X_i + Rand() \cdot Step & otherwise \end{cases} \tag{7}$$

Wherein, *Rand* () is a random number in the (0,1) range; *Step* is the step length [15].

(2) Swarm behavior. Let the number of partners within the vision scope of the artificial fish be n_f, and the central position be X_c, and if $Y_c/n_f > \delta Y_i$ (δ is the crowding degree factor), it indicates that the food density of partners is greater, so it will make a step forward to the center of the partners, or perform the foraging behavior:

$$\begin{cases} X_{i|next} = X_i + Rand() \cdot Step \cdot \dfrac{X_c - X_i}{\left\| X_c - X_i \right\|} & ,Y_c / n_f > \delta Y_i \\ \text{觅食} & otherwise \end{cases} \tag{8}$$

(3) Rear-ending behavior. Let the position of the artificial fish Y_j within the vision range of which the food density is the highest be X_{max}, if $Y_j/n_f > \delta Y_i$, X_j will make a step forward, otherwise perform the foraging behavior.

$$\begin{cases} X_{i|next} = X_i + Rand() \cdot Step \cdot \dfrac{X_{\max} - X_i}{\left\| X_{\max} - X_i \right\|} & ,Y_{\max} / n_f > \delta Y_i \\ \text{觅食} & otherwise \end{cases} \tag{9}$$

(4) Random behavior. Artificial fish randomly selects a state within the visual range and then moves to the direction, which is the default behavior of foraging behavior.

(5) Bulletin board. Bulletin board is used to record the state of the best artificial fish.

3.2. Procedure for LSSVM parameters optimization by AFSA

(1) Initialization of artificial fish parameters mainly include the moment step length: Step, the population size: n, the maximum iterations: max_iterate.

(2) Within the feasible extension, n of artificial fish are generated randomly, and the initial position of the fish is (γ,σ) , then according to the combination value of the parameter (γ,σ) which will be taken as LSSVM parameter, the LSSVM will be adopted for training and modeling, and the prediction result of the sample will be obtained through the model.

(3) The fitness function will be calculated according to formula(10), and the individual artificial fish with maximum fitness function value will be selected to make entry into the annunciation board. In the formula (10), **Error! Reference source not found.** is the distance vector from the node to each beacon node; fx, fy and fz are the estimation value of regression model which is established by means of optimization modeling parameters.

$$FC = \sqrt{\frac{1}{M}\sum_{l=1}^{M}((f_x(R_l') - x_l')^2 + (f_y(R_l') - y_l')^2 + (f_z(R_l') - z_l')^2)} \qquad (10)$$

(4) The artificial fish has simulated the fish-feeding, rear end and clustering behavior of fish group to obtain the new artificial fish position.

(5) Make comparison with the artificial fish position in the annunciation board, provided that it is superior to that in the annunciation board, this artificial fish position will be recorded and entered into the annunciation board.

(6) Make decoding of the best position in the annunciation board to obtain the optimum LSSVM parameters (γ,σ).

(7) Use the optimum parameters to establish the optimum sensor location model, and m ake testing on its performance.

4. Simulation Experiment

4.1. Simulation Environment

In order to test the advantages and disadvantages of the properties of AFSA-LSSVM th ree-dimensional sensor positioning method, under Windows XP operating system, use the Matlab 2012 Toolkit for simulation experiments. 200 sensor nodes are distributed randoml y within the 3-dimension range of 100m×100m×100m, the number of unknown sensor no des is 150, the number of beacon nodes with known position information is 50, choose the least square (LS) method and use the least square supported vector machine(LSSVM) op timized by the grid search algorithm to make comparison experiment, all the methods will be repeated for 10 times, and the average positioning error will be taken as the evaluatio n criterion.

4.2. Result and Analysis

4.2.1. The Influence on the Positioning Error by the Distance Measuring Error

Under different distance errors, the positioning error of LS, LSSVM and AFSA-LSSVM is shown as figure 2. It is can be known from Figure 2 that with the increasing of distance error, the node positioning error of LS, LSSVM and AFSA-LSSVM tends to be increased, and the positioning precision is gradually decreased, while compared with LS and LSSVM, the positioning property of AFSA-LSSVM has been improved and the positioning error has been significantly reduced. The comparison result has shown that using AFSA to make optimization on LSSVM parameters can obtain better LSSVM parameters, thus the better sensor node positioning model can be established, even in the harsh environment in which the distance measurement error can not meet the positioning requirement, AFSA-LSSVM is still able to realize positioning and has quite strong anti-interference ability to get better positioning effect.

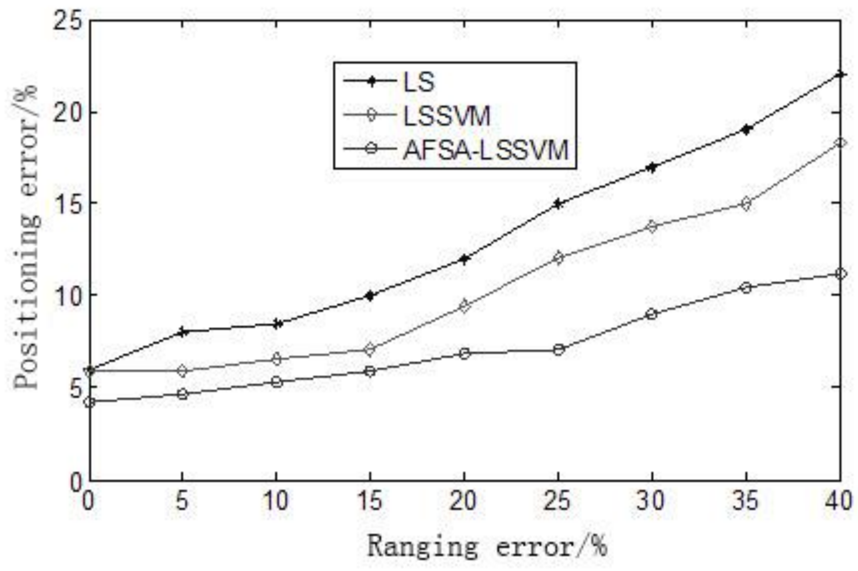

Figure 1. The Influence of Ranging Error on Positioning Accuracy

4.2.2. Comparison of Positioning Error under Different Communication Radius

Under different communication RADIUS, LS, AFSA-LSSVM and LSSVM positioning errors are shown as Figure 2. It can be known from Figure 3, with the increasing of communication radius, due to the increment of positionable beacon nodes number of unknown nodes as well as the increasing of signal strength at the same time and thus the more accurate positioning, the positioning error of sensor nodes of 3 methods is reduced gradually, and the positioning precision continues to be raised. In the meanwhile, compared to the contrasting approaches, the positioning error of AFSA-LSSVM is lowest and its positioning accuracy is highest.

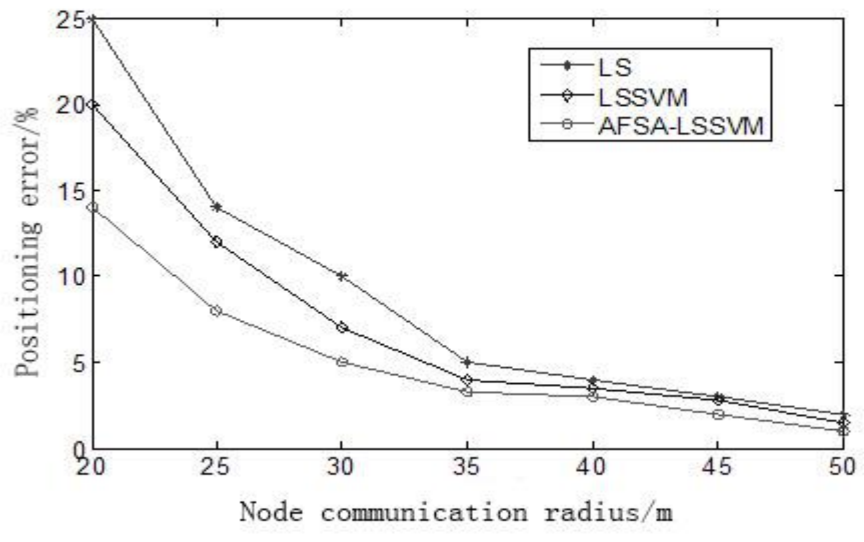

Figure 2. The Influence of Communication Radius on Positioning Accuracy

4.2.3. Comparison of Positioning Error between Different Beacon Node Density

Because the beacon node location information needs to employ special positioning equi pment to acquire, if the beacon node number is increased, it will lead to the huge augment ation of sensor application cost. Under different beacon node density, the LS, AFSA-LSS VM and LSSVM positioning error changes are shown in Figure 3. It can be seen from fig ure 3, with the increasing of beacon nodes density, the positioning error of all methods is gradually reduced. Compared with the contrasting approaches, the positioning error of AF SA-LSSVM is the lowest and its positioning accuracy is the highest. At the same time, in case that the beacon nodes density is higher than 100%, the positioning accuracy of AFSA -LSSVM can reach over 95%, and the comparison result has shown that the AFSA can res olve the LSSVM parameters optimization problem quite well. AFSA-LSSVM is a kind of sensor beacon node positioning method with high positioning accuracy and low cost, whic h has not much requirement on beacon node density and is suitable for the network enviro nment with sparse nodes.

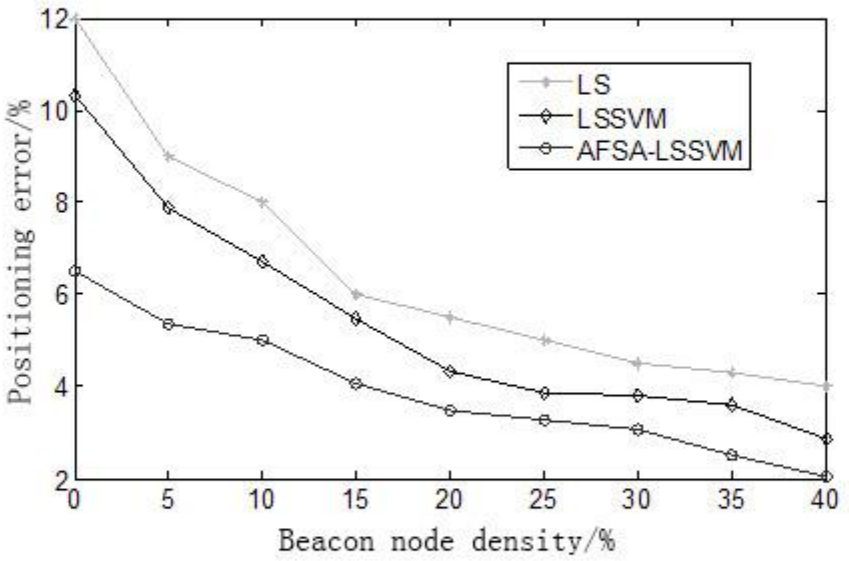

Figure 3. The Influence of Beacon Node Density on Positioning Accuracy

5. Conclusion

Node positioning is the basis for the application of WSN. With regard to the parameters optimization of LSSVM in the sensor node positioning process, a three-dimensional AFS A optimized LSSVM WSN node positioning method is proposed. The simulation results s how that compared with the methods for comparison, AFSA-LSSVM which requires fewe r beacon nodes can achieve highly precise positioning results. It not only is more competit ive in robustness of positioning but also can reduce the cost of the sensor node positioning , which is available for the network node positioning of all types of wireless sensors and h ighly applicable.

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