

A kind of PSO-LSSVM Node Positioning in Wireless Sensor

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Abstract: In order to improve the positioning accuracy of wireless sensors, and aiming at the parameter optimization problem of least squares support vector machine (LSSVM), a node positioning of particle swarm optimization's optimized LSSVM sensor is proposed. First, two-dimensional wireless sensor positioning model sample is established, and then LSSVM is adopted to establish node positioning model and PSO algorithm is used to find the optimal parameter. Finally, node's performance of positioning is tested by simulation experiment. Compared with other positioning method, PSO-LSSVM improves the positioning accuracy of sensor node with some certain practical application value.

Keywords wireless sensor network; node positioning; least squares support vector machine

INTRODUCTION

Node localization technology has always been the key technology of Wireless Sensor Network (WSN), and with the constant expansion of WSN's application range, node localization may have some shortcomings like inaccurate node localization, poor localization effect, and inaccurate data transmission effect. Therefore, to improve the accuracy of sensor node has become the hot issue in WSN research [1-2]. For localization of WSN nodes, many scholars conducted extensive research and made a number of node localization algorithm. Literature [3] proposed a PSO of multidimensional scaling node localization algorithm, which does not require distance, simple and easy to implement, but the localization accuracy and anchor nodes closely related to less robust. Literature [4] proposed WSN node localization method based on multidimensional scaling, multiple iterations of the method, high computational complexity, it is difficult to meet the requirements of real-time sensor node localization. Literature [5] proposed a hop away from the proposed amendments, a localization based on particle swarm optimization algorithm WPDV-Hop, but to achieve more complex range of applications is limited. Literature [6] proposed a grouping Particle Swarm Optimization (GPSO), which does not require additional hardware, low cost, but adversely affected by the accumulated error of localization results are not satisfactory.

LSSVM'S WSN NODE LOCALIZATION METHODS

Anchor Node Data Packaging Broadcasting Phase

WSN broadcasting of anchor node contains data packaging of its own information. After the node has received information, its hop account increases by 1 and continues its sensor node broadcasting until the broadcasting covers all the network [11].

Calculate the Distance of Each Hop

According to otehr anchors' location information and hop account, calculate the average network hop distance of each unknown node through formula (1):

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

In the formula, j refers to other anchors' node number of unknown node i in the table and hopS_{ij} refers to the hop amounts between anchor I and j.

After the anchor node broadcasts the average hop to the entire network, unknow nodes only record the first average hop distance, and then forward to the neighbor node, the unknown node receives the average hop distance, according to the records of the number of hops (2) to estimate the distance of the unknown node i to an anchor node:

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

LSSVM Establishes Models and Localize Nodes

(1) Suppose the distance between the underdetermined node $S'_l(x'_l, y'_l)$ and $(l = 1, 2, \dots, M)$ and $S_j(j \in 1, 2, \dots, M)$ the anchor node as d'_{ij} . Then, the vector of distance between S'_l and each anchor as $R'_l = [d'_{l1}, d'_{l2}, \dots, d'_{lM}]$. Construct training sample set $U_x = \{(R'_l, x'_l) | l = 1, 2, \dots, M\}$ and $U_y = \{(R'_l, y'_l) | l = 1, 2, \dots, M\}$ with M underdetermined localization nodes' distance vector R'_l and its coordinate (x'_l, y'_l) .

(2) Train sample set UX and UY respectively using LSSVM, construct UX and solve the optimal problem as shown in formula (3).

$$\min_{\omega, \xi, b} \frac{1}{2} \|\omega\|^2 + \gamma \frac{1}{2} \sum_{i=1}^M \xi^2$$

s.t. (3)

$$x'_l = \omega^T \phi(R'_l) + b + \xi_l$$

$$l = 1, 2, \dots, M$$

There are many current LSSVM kernel, its radial basis function with parameters, versatility, etc., paper chooses as LSSVM kernel function, specifically defined as follows:

$$K(R'_m, R'_n) = \exp\left(-\frac{\|R'_m, R'_n\|^2}{2\sigma^2}\right)$$

(m, n = 1, 2, ..., M) (4)

Convert formula (3) as a dual problem by introducing Lagrange operator a and b, that is

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

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

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

$$\hat{x} = f_x(R) = \sum_{l=1}^M a_l K(R_l, R'_l) + b \quad (6)$$

(4) The distance of unknown node Si to each anchor node is dij, constituting distance vector as Ri=[di1, di2, ..., diL] as the output vector of decision functions fx and fy, get the estimate coordinate value of unknown node Si of \hat{x}_i and \hat{y}_i , that is (\hat{x}_i, \hat{y}_i) .

PSO-LSSVM

From LSSVM modeling process, radial basis function σ and regularization parameter γ value on LSSVM greater performance, currently often used a grid search algorithm, genetic algorithms and artificial fish swarm algorithm to solve the parameters, time-consuming, prone get local optimal solution, given the PSO has strong global search capability, but also has the advantages of simple and easy to implement, we use PSO to optimization of LSSVM parameters LSSVM find the optimal parameters in order to improve the positioning accuracy of the sensor node.

PSO

Particle Swarm Optimization (PSO) is an analog birds looking for food in the process, in the algorithm, optimized solution for each problem is a bird in the search space, these birds called "particle." All particles by an optimized adaptation value (fitnessvalue) function is determined, as well as a speed determines the direction and distance they fly. Then the particles were then follow the current optimal particle search in the solution space. The space is a no individual compared to the quality and volume of the particles. Set the i particle in the group as $x_i = \{x_{i1}, x_{i2}, \dots, x_{im}\}$, and its location as $p_i = \{p_{i1}, p_{i2}, \dots, p_{im}\}$. Herein, the optimal location as p_{gbest} . The optimal location of all the particles in the current group as p_{gbest} , and the particle i is shown as $v_i = \{v_{i1}, v_{i2}, \dots, v_{in}\}$. The motion formula of particle i is:

$$v_{id}(t+1) = w \times v_{id}(t) + c_1 \times rand() \times (p_{best} - x_{id}(t)) + c_2 \times rand() \times (p_{gbest} - x_{id}(t))$$

(7)

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (8)$$

Herein, w refers to the inertia weight, c_1 and c_2 as constants, and $rand()$ as a random number valued between (0,1).

Steps for PSO to Optimize LSSVM

(1) Initialize particle swarm algorithm's parameter, set the group scale as n, and the maximum iteration times as max_iterate, set c_1 and c_2 as a number between [0,1], and w as 0.5.

(2) Randomly generate n particles within the range of feasible region, their initial position (γ, σ) , according to (γ, σ) value as a parameter combination LSSVM parameters, and then use LSSVM training and modeling, and has been the model of the sample the forecast results.

(3) Calculate the fitness function according to formula (9) and select individual particles with the maximum fitness value to enter the bulletin board.

$$FC = \sqrt{\frac{1}{M} \sum_{l=1}^M ((f_x(R'_l) - x'_l)^2 + (f_y(R'_l) - y'_l)^2)} \quad (9)$$

In the formula, R'_l refers to the distance vector of unknown nodes to each anchor node, while f_x and f_y refer to the estimated value of regression model established by optimization modelling.

(4) Get the particle's new speed and location through formula (7) and (8).

(5) Compare with the original particle's location and speed; if it is superior to the original value, replace this particle's original speed and location.

(6) Decode the speed and position of the optimal particle to get the optimal parameter (γ, σ) of LSSVM.

(7) Establish the optimal sensor localization model using the optimization parameter and test its performance.

SIMULATION EXPERIMENT

Simulation Environment

To test the performance of PSO-LSSVM localization of sensor nodes the merits, under Windows XP operating system, using Matlab 2012 toolbox simulation. 200 sensor nodes randomly distributed in the two-dimensional area $100m \times 100m$, unknown sensor nodes 150, anchor nodes known location information is 50, the paper selection method of least squares (LS), grid search algorithm optimization minimum two support vector machine (LSSVM) comparative tests, running a total of 100 times, select the average location error as the evaluation criteria.

Results and Analysis

Grid search algorithm and the PSO optimization parameters of LSSVM processes such as shown in Figure 1, the network search algorithm to get the parameters of LSSVM $\gamma = 187.18$, $\sigma = 1.25$, PSO is applied to get the parameters of LSSVM $\gamma = 127.65$, $\sigma = 1.970$. From Figure 1, we can see that the search speed of PSO is significantly better than the network search algorithm, and get smaller root mean square error, which indicates that the PSO algorithm is better than the LSSVM algorithm, which can improve the accuracy of sensor node localization.

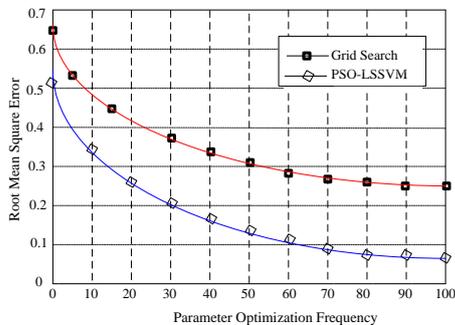


Fig.1 Grid Search Algorithm and Particle Swarm Algorithm's Optimization Process

With different distance errors, LS, LSSVM and PSO-LSSVM positioning error shown in Figure 2. Figure 2 shows that with increasing distance error, LS, node localization error LSSVM and PSO-LSSVM's tended to increase positioning accuracy decreased, but compared with the LS, LSSVM, PSO-LSSVM positioning performance has been improved, positioning a significant reduction in

errors, compared to the results show that the PSO optimized for LSSVM can get a better LSSVM parameters, which can establish a better actor sensor node localization model and PSO-LSSVM able to achieve a better position, It has strong anti-jamming capability, access to the better positioning effect.

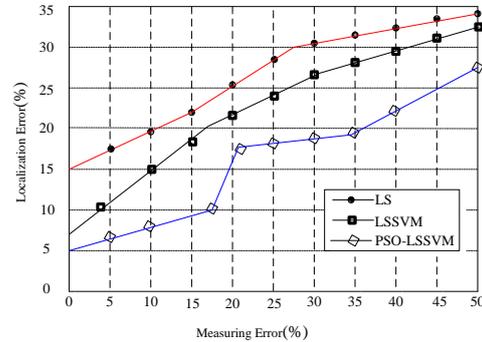


Fig.2 Measuring Error's Influence on Localization Accuracy

CONCLUSION

Node localization is the basis for the application of wireless sensor networks. In the process of sensor node localization, a new LSSVM WSN LSSVM node localization method based on PSO is proposed. The simulation results show that, compared with the contrast method, PSO-LSSVM needs fewer anchor nodes to obtain high precision localization results, which not only can be more robust, but also reduces the cost of sensor node localization.

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