Optimization of immune particle swarm algorithm and application on wireless sensor networks

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Abstract

As a new network technology, wireless sensor network (WSN) have been applied to military, intelligent transportation, environmental monitoring and other fields. Localization is one of the important support technologies of Wireless Sensor Networks. Location information is important to network monitoring. It is meaningless, if there is no location information. We need to adopt a certain mechanism and algorithm to implement the localization of Wireless Sensor Networks. Based on the analysis of the features of Wireless Sensor Networks on range-free positioning algorithm and DV-Hop positioning algorithm error sources, this paper focuses on the improvement research on DV-Hop positioning algorithm. Inspired by biological immune system and mechanism, this paper introduces the immune information processing mechanisms in the immune system to the particle swarm optimization algorithm and thus gets an immune particle swarm optimization (IPSO) algorithm. By applying into the running of DV-Hop positioning algorithm, the paper proposes a DV-Hop improved algorithm, which is, the WSN positioning algorithm based on IPSO algorithm. Simulation experiments show that the improved algorithm can significantly reduce positioning errors to improve positioning accuracy.

Keywords: wireless sensor networks, immune particle swarm optimization, DV-Hop positioning algorithm

1 Introduction

Wireless Sensor Networks positioning control is a basic problem in WSN applications. It is a study on how to maximize the network coverage to provide reliable monitoring and tracking services in the guaranteed quality of service conditions. Effective strategies of the coverage control and algorithms can be used to optimize the allocation of resources of WSN, increase the efficiency of the energy usage of network nodes, and improve the perceived quality of service and the overall survival time. How to combine different environmental demands and design a practical strategy for positioning is a significant research field.

Particle Swarm Optimization (PSO) have the advantages of natural paralleled, strong robustness, and global optimization, and have obvious advantages in dealing with the complex problems. Therefore, the PSO will be very suitable to solve the nodes positioning problem in the WSN. This paper makes the investigations on the PSO in solving the nodes positioning problem in the WSN, and proposes coverage mechanism based on an immune particle swarm optimization algorithm to optimize the problem. The paper gives a review on the WSN and its nodes optimal coverage problem. Moreover, the implementation details for the IPSO solving the nodes optimal positioning are described, including the particle code representation, and the complete algorithm flowchart. Simulations have been conducted and the results are compared with the ones obtained by other algorithms. The experimental results and comparisons demonstrate the effectiveness and efficiency of our proposed algorithm.

At last, based on simulation platform, the paper makes a simulation experiment on the existing DV-Hop improve algorithms and the new DV-Hop positioning algorithm based on IPSO algorithm. Through the simulation experiment results, this paper analyses the merits of the IPSO algorithm. This paper is highlighted with the contributions to the theoretical researches and practical applications of the PSO and the WSN as follows: Firstly, the IPSO is successfully applied to provide a new solution to the nodes optimal positioning in the WSN. Secondly, the proposed algorithm is simpler than the traditional algorithms, and with a higher computational effectiveness. Thirdly, the proposed algorithm has a better performance that can obtain higher positioning accuracy.

2 Basic particle swarm optimization

The basic PSO could be described as follow: supposing in a n-dimension research space, the population is $X=\{x_1,...,x_i,...,x_m\}$, among which the position of I particle is $X_i=\{x_{i1},x_{i2},\cdots,x_{in}\}^T$, the speed is $v_i=\{v_{i1},v_{i2},\cdots,v_{in}\}^T$, the individual extremum is $p_i=\{p_{i1},p_{i2},\cdots,p_{in}\}^T$, the global extremum is $p_g=\{p_{g1},p_{g2},\cdots,p_{gn}\}^T$. Based on the principle of following the optimized particle, the particle X_i will change

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the speed and position in accordance with the following Equation, as is shown in the Figure 1:

$$v_{id}^{(k+1)} = v_{id}^{(k)} + c_1 r_1 (p_{id}^{(k)} - x_{id}^{(k)}) + c_2 r_2 (p_{gd}^{(k)} - x_{id}^{(k)}) . \quad (1)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)} . \quad (2)$$

In the Figure 1, m is the sum of the particles in the population. d=1,2,…,n, n is the dimensions of particle search space. $v_{id}^{(k)}$ is the iterative particle i's Flight velocity vector's d dimension component at the K time, which is between $-v_{d\max}$ and $v_{d\max}$. $v_{d\max}$ could be set according to different controlling variables by the users. $x_{id}^{(k)}$ is the iterative particle i's d dimension component at the K time. $p_{id}^{(k)}$ is the iterative particle i's best position at the K time p_{best} 's d dimension component. $p_{gd}^{(k)}$ is the iterative group's best position at the K time g_{best} 's d dimension component. c_1, c_2 is the learning factor or speeding up factor. r_1, r_2 is the random figure among [0,1] produced by random function [1, 2].

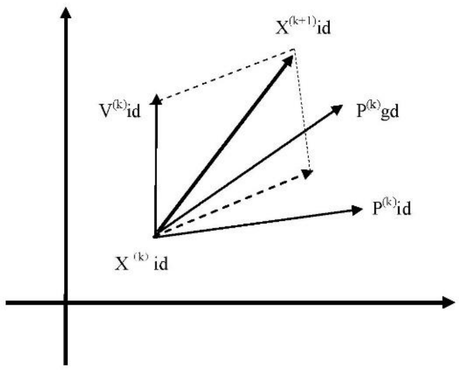

FIGURE 1 The d dimension variable diagram of basic particle

In Equation (1), a constant inertia weighting factor ω could be added before $v_{id}^{(k)}$. Normally, the ω's Figure 1 and Figure 2 is the formula of basic particle swarm algorithm formula.

In Equation (1), three are three parts to calculate the new speed of particle i: the first part is the $\omega v_{id}^{(k)}$, the speed at the former time, indicating the status of the particle at that moment. The second part is the $c_1 r_1 (p_{id}^{(k)} - x_{id}^{(k)})$, the distance of the current position and the best position of particle i, which is the part for self-recognition, indicating the thoughts for itself. The third part is the $c_2 r_2 (p_{gd}^{(k)} - x_{id}^{(k)})$, distance of the current position of particle i and the best position of the group, which the social part and the best vector from current point to the group, indicating the cooperation and knowledge share between particles.

All the three parts determine the spatial search capabilities of the particles. The first part has played a role in the balance of global and local search capability; the second part of the particles has a sufficiently strong global search capability; third part reflects the sharing of information between the particles. Under the combined effect of these three parts, the particles thus could effectively reach the best position. Particle i calculates the coordinates of the new location by the Equation (2), and determines the position and velocity of movement next by Equations (1) and (2).

There are few parameters need to be adjusted in PS algorithm. But the setting on the parameters makes a great impact on the performance of the algorithm. The parameters as well as experience setting are listed below: inertia weight ω has a better performance in [0.9, 1.2], and performs better from 1.4 to 0 than the fixed. The largest speed $v_{d\max}$ also influences the ω, generally speaking, when the $v_{d\max}$ is small, ω is about 1 and when $v_{d\max}$ is big, the ω is about 0.8 with the better performance of PSO algorithm.

Learning factor c_1 and c_2 are used to control the particle's own memory and the memory of companions. Selecting the appropriate algorithm can improve the speed and avoid local minima. Experiments showed that $c_1 = c_2 = 2$ or $c_1 = c_2 = 0.5$ is a good choice, but $c_1 + c_2 \le 4$ is better.

When the particles constantly adjust their positions according to the speed, they are restricted by the maximum speed $v_{\max}$. When $v_{id}^{(k)}$ exceeds $v_{d\max}$, the particles would be defined as $v_{d\max}$. Maximum speed $v_{d\max}$ determines the maximum travel distance of the particles in a loop, which typically should not exceed the width of the particles. If $v_{d\max}$ is too large, the position of the particle may fly optimal solution; If $v_{d\max}$ is too small, it may reduce the global search ability of particles [3].

Particles flying speed cannot exceed the maximum speed $v_{d\max}$ of the algorithm set. In general, in

$$v_{\max} = (v_{1\max}, ..., v_{d\max}, ..., v_{n\max})^T =$$
$$a * (v_{1\max} - v_{1\min}, ..., v_{d\max} - v_{d\min}, ... v_{n\max} - v_{n\min})^{T_1}$$

$x_{d\max}$ and $x_{d\min}$ represent the upper and lower limit values of the particles of the d-dimensional variables. a is a control factor, 0<a<1. Setting a large $v_{\max}$ could promote the global search capability of particle populations, while when $v_{\max}$ is small, the local search capability could be strengthened. The numbers of particles (population size or population size) generally could use 20~60. For general optimization problems, 10 particles are enough. For some special problems, the number of particles can take up to 100~200. Particle dimension is determined by the dimension of the optimization problem (solution space dimension) [4].

3 Immune particle swarm optimization process

The design flow chart of IPS algorithm used in this paper is as shown in Figure 2:

1) Initialization parameters. The algorithm is given an initial value of the inertia factor $\omega(0)$, the acceleration factor c_1, the number of immune population of particles N, the maximum number of iterations (the number of generations) K_{max} and other parameters.

2) Initial antibody (population) yields. N immune particles are randomly generated and the "flying" speed is V_i, so that to form the initial immune particle population P_0. Set the value of each individual particle initial immunization optimal solution P_{best} and the global optimal solution G_{best}.

3) Antibodies fitness evaluation. In the current population, to calculate all antibodies (immune particle) fitness. In the immune particle swarm algorithm, the fitness function usually takes the transformation of some function's objective function which needs to be optimized [5]. In the design of the main fitness function, it should satisfy the following conditions:

a) Reasonable and conformed requirements. The fitness should reflect the degree of solution of the pros and cons of the corresponding value solution; small;

b) small task of calculation. The amount of the fitness function should be designed as simple as possible;

c) strong versatility. The fitness for certain specific issues should be commonly used as possible as it can.

d) Calculation of antigen and antibody binding strength and concentration of antibody. Corresponding antigen immune system optimization objective function corresponding antibody solution optimization problems. To decide antigen and antibody binding force based on the value of the objective function; to decide the binding force of the antibody based on the degree of similarity solution and use the combination of these two forces to make solution evaluation and selection.

The binding force between antibody and antigen is defined as A_v, and could be changed by the target function into:

$$A_v = \mu[f(v)]. \tag{3}$$

In Equation (3): $f(v)$ is the target function, $\mu(x)$ is the monotone function of x, which reflects the evaluation to the target function [6].

This article taken sorting selection method, the size of the binding force A_v between the antibody and antigen has no absolute meaning. A_v value does not need to guarantee positive, so the reactive power optimization problem studied in this paper can be the binding force A_v between the antibody and antigen and directly take reactive power optimization objective function model:

$$A_v = f(v). \tag{4}$$

Process of solving the objective function is as follows: the control variable is calculated based on the decision of the antibody, and then derived value of the state variables into the objective function optimization problems. Then put the objective function into the Equation (4), which can obtain antigen and antibody binding force. Since the target function of this paper is to get the minimum value of the solution function, the smaller the antigen and antibody binding force, the closer the optimal solution antibody to the optimization.

The binding force between the antibodies reflects the degree of similarity. When two antibodies are similar, the binding force is larger, on the contrary, the smaller, as is shown in the following equation:

$$B_{v,w} = \frac{1}{1+H_{v,w}}. \tag{5}$$

$H_{v,w}$ is the vector from the definition of the two antibodies type. In this paper, Euclidean space 2-norm can be used to define the sense of distance:

$$H_{v,w} = \left\{\sum[(V_{Giv} - V_{Giw})^2 + (D_{civ} - D_{ciw})^2 + (T_{iv} - T_{iw})^2]\right\}^{\frac{1}{2}}. \tag{6}$$

Thus the calculation of antibody density c_v could use the following Equation:

$$c_v = \frac{\sum_{w=1}^{N} B_{v,w}}{N}. \tag{7}$$

N is the number of antibody populations. The larger the concentration of the antibody is, the greater the similarity of such antibodies and other antibodies is.

5) Memory structure and unit prohibition. The largest concentration of antibody population antibody showed that it accounted for in the antibody group in an absolute advantage, namely to achieve a relatively optimal solution, which reflects the evolution of the results of this generation of population. The largest concentration of antibody should be retained by the principle to retain it which is the role of memory structure. The high concentration of antibodies and other antibodies showed large similarities between large groups, in order to maintain the diversity of the antibody, it needs higher concentrations of antibody suppression. Setting the antibody according to the size of its concentration, the author sort through the set-out rate (This article set it as 10%), finding that the higher concentrations of antibodies were eliminated and new randomly generated antibodies and antibody replaced the eliminated. Inhibiting the high concentrations of antibodies can well prevent the development of antibodies from being a single group so as to maintain the antibody population diversity and avoid local optimal solution. That is the role of inhibition of cell.

Fitness value of antibody v showed its performance. The fitness value calculation function could be formed by the binding force A_v and the concentration c_v:

$$p = \alpha A_v + (1-\alpha)c_v. \tag{8}$$

α is a scaling factor ($0 < \alpha < 1$) antibody V's adaptation has the following characteristics: the smaller the antibody and the antigen binding capacity A_v, the smaller the value of the corresponding adaptation; the smaller the antibody concentration, the smaller the value of the corresponding adaptation; the smaller the adaptation value, the closer the near-optimal solution. Setting the size of α could adjust the weight between antibody-antigen binding force and concentration, which can also retain the antigen binding force small (i.e., the objective function value is small) antibodies, but to ensure the diversity of individuals through inter-antibody concentration based on mutual promotion and inhibition mechanisms, so that the optimal solution for improving the convergence of favorable vicinity [7].

6) Group updating and the generation of new immune particle. To update particle speed and produce new immune particle N in accordance with the following equation:

$$v_{idid}^{(k+1)} = \omega^{(k)} v_{id}^{(k)} + c_1 r_1 (p_{id}^{(k)} - x_{id}^{(k)}) + c_2 r_2 (p_{gd}^{(k)} - x_{id}^{(k)}) \quad (9)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)} \quad (10)$$

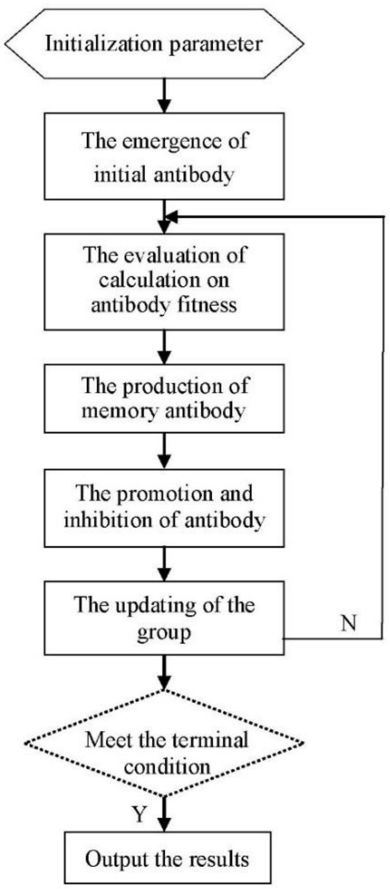

FIGURE 2 The flow chart of immune particle swarm optimization algorithm

PSO in the early age has a fast convergence but has a not high accuracy in the late convergence stage, which is easy to fall into local optimum. Therefore, the author designed the inertia factor ω, which will have a great impact to optimize the performance of the algorithm. The large ω values could help to improve the convergence speed while the small ω could help to improve the convergence of the algorithm accuracy. According to this feature, this paper used the Equation (11) to improve ω, so that it can adaptively adjust to achieve the purpose of decreasing ω with the increasing of the value of the iterations

$$\omega^{(k)} = (2/(1+e^{\sigma k/K\max}))\omega(0)\,. \quad (11)$$

σ is the positive coefficient; K_{max} is the set maximum number of iterations (the number of generations); $\omega(0)$ is the initial value; k is the current iteration [8].

7) To judge if it meets the termination condition. If being satisfied, to stop the running and put out the results, otherwise, go to step 3.

4 Simulation of improved algorithm

In order to evaluate the performance of immune particle swarm optimization algorithm, this paper makes a comparison on the DV-Hop algorithm based on IPSO and several other DV-Hop algorithms through simulation experiment. In the simulation, all the sensor nodes are arranged in the 100M, 100M square area. According to the relevant literature, anchor nodes arranged in a border area is relatively good accuracy. For this case, the paper put 100 unknown nodes and anchor nodes evenly on the boundary of the square area. The total proportion of the anchor node of the node changes as the experimental conditions.

While maintaining the other parameters constant, the author changed the proportion of anchor nodes in the total nodes, the communication range of the unknown nods and the three parameters respectively to make simulation experiments. Meanwhile, in order to make the results more convincing, this paper made a simulation experiment on the DV-Hop positioning algorithm based on IPSO and the improved several DV-Hop algorithms under the same experimental conditions and then made an analysis on the positioning results. By making a plurality of simulations on the same algorithm, the author took the average value of the final simulation results in order to reduce the error caused by the experiment itself and make the results more accurate. In the immune particle swarm optimization algorithm, the number of particles is 30, the largest and the smallest particle fitness values were max, min.

4.1 THE RELATIONSHIP DIAGRAM OF THE ANCHOR NODE PROPORTION AND THE AVERAGE POSITIONING ERROR OF THE NODE

Figure 3 shows the relationship diagram of the anchor node proportion and the average positioning error of the node. From this, it can be seen as follows:

(a) The positioning error ratio of several positioning algorithms decreased with of increasing of the anchor nodes. That is because if the anchor node ratio increases, it will provide more information and the corresponding positioning accuracy would be promoted. There is an extreme case, when all nodes are anchor nodes, the node can position itself, which is also conformed with the achievement situations.

(b) When the proportion of the anchor nodes is the same, the improved DV-Hop algorithm has a smaller positioning error compared to the original location DV-Hop algorithm, among which the DV-Hop algorithm based on immune particle swarm optimization has the minimal positioning error, which also shows a good performance of IPSO.

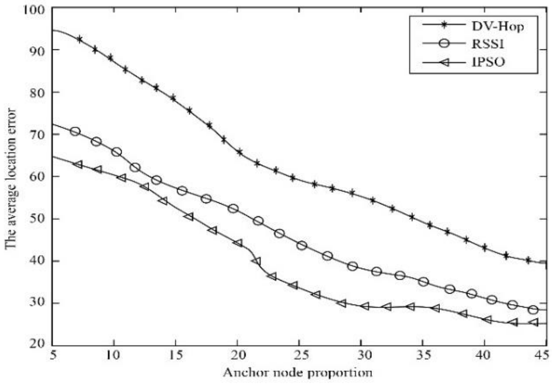

FIGURE 3 The relationship diagram of the anchor node proportion and the average positioning error of the node

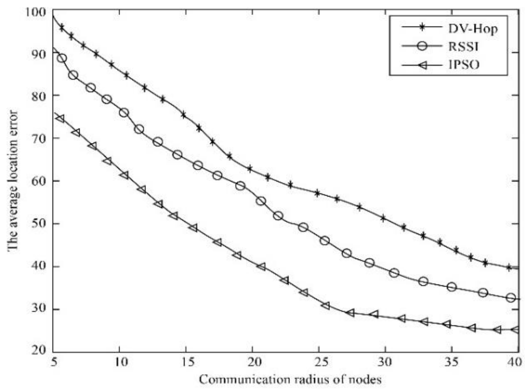

FIGURE 4 The relationship diagram of the communication radius and the average location error of the node

4.2 THE RELATIONSHIP DIAGRAM OF THE COMMUNICATION RADIUS AND THE AVERAGE POSITIONING ERROR OF THE NODE

Figure 4 shows the relationship diagram of the communication radius and the average positioning error of the node. From this, it can be seen as follows:

(a) The positioning errors of the shown positioning algorithm declines with the expansion of the unknown node communication radius for the expansion of the unknown node communication radius strengthens the corresponding connectivity of the unknown node with other nodes, thus the node can get a larger range of information exchange and to improve the positioning accuracy of the algorithm.

(b) Although the positioning errors of several positioning algorithms were decreased, it is relatively small, because even though the communication range of the node were increased to some extent, the exchange information of the number of the anchor node exchanged with the unknown node may be increased. And not every anchor node can provide useful information for locating the unknown nodes.

4.3 EFFECT OF TOTAL NODES ON AVERAGE POSITIONING ERROR OF THE NODE

Figure 5 shows the relationship diagram of total number of nodes and average positioning error. From this, it can be seen as follows:

(a) When the total number of nodes increases from 5 to 30, the positioning of several errors in the positioning algorithm has a certain impact. The average error of nodes declines with the increasing of the total number of nodes.

(b) With the change of the total number of nodes, the magnitude of change in average bit error localization algorithm is relatively large, which also reflects the scalability of the algorithm needs to be further improved.

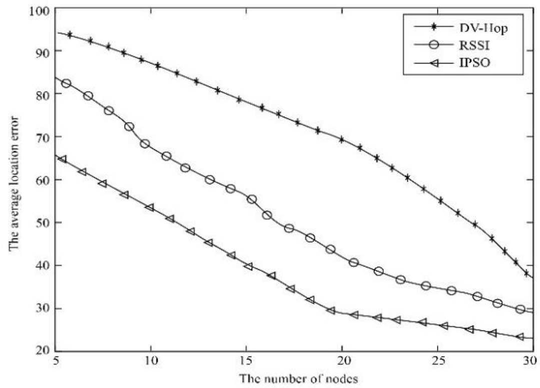

FIGURE 5 The relationship diagram of total number of nodes and average location error

5 Conclusion

This paper introduced the research background and research status at home and abroad for the WSN, and then introduced the Wireless Sensor Networks characteristics, as well as its structure and key technologies. While making a classification on positioning algorithms, this paper illustrated the basic principles of the typical positioning algorithm. On the basis of the analysis of the basic ideas of immune particle swarm optimization, this paper analysed the positioning error sources of DV-Hop positioning algorithm. By combining with the characteristics of immune particle swarm optimization algorithm, this paper proposed a new DV-Hop algorithm based on immune particle swarm optimization algorithm. Finally, the simulation experiments showed that the improved algorithm can significantly reduce positioning errors to improve coverage accuracy.

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